Exhibit 2

Declaration of David Cutler in Support of Plaintiffs' Memorandum in Opposition to Defendants' Motion to Exclude David Cutler's Opinions and Proposed Testimony

I. Introduction and Overview

1. My name is David Cutler. I am the Otto Eckstein Professor of Applied Economics and Harvard College Professor at Harvard University. I submitted a report in this matter on March 25, 2019 that evaluated the impact of prescription opioid shipments on harms that impose costs on Bellwether jurisdictions.[1] That report and supporting materials describe my analysis and conclusions and summarize my qualifications. I submit this declaration in support of Plaintiffs' Memorandum of Law in Opposition to Defendants' Motion to Exclude David Cutler's Opinions and Proposed Testimony.

2. I have been asked by counsel for the Bellwether governments to review and respond from an economic perspective to the defendants' motion to exclude my opinions and proposed testimony.[2] Defendants argue that my testimony should be excluded because:

- My analysis does not "fit the case" and "fails to link any Defendant's alleged misconduct to any harms in the Track One counties."[3]
    - They claim that there is "no input Cutler can insert into his model to link the harms he analyzes to any alleged misconduct."[4]
    - Defendants further claim that my analysis "makes no attempt to isolate whether any particular defendant's conduct caused any 'harms' in the Track 1 counties."[5]
- My analyses "contain incurable methodological failures." Defendants' argue:
    - My analysis uses a "national regression models to estimate the percent of harms caused by Defendants' alleged misconduct in two specific counties – Cuyahoga and Summit."[6] They claim that the use of an "aggregate model" is "impermissible and irrelevant."[7]

[1] Expert Report of Professor David Cutler, March 25, 2019 ("Cutler Report" or "March 25 Report" or "Report").
[2] Memorandum in Support of Defendants' Motion to Exclude David Cutler's Opinions and Proposed Testimony ("Defendants' Daubert Motion"), June 28, 2019.
[3] Defendants' Daubert Motion, p. 1 and 3.
[4] Defendants' Daubert Motion, p. 2.
[5] Defendants' Daubert Motion, p. 3.
[6] Defendants' Daubert Motion, p. 11 and 13.
[7] Defendants' Daubert Motion, p. 7.

- My regression analyses suffer from "omitted-variable bias" including the failure to adequately consider the relationship between opioid-related mortality and other types of "deaths of despair";[8]
- My analysis is based on "the unsupported theory that Defendants are responsible for all illegal opioid overdose deaths …";[9]
- My analysis inappropriately uses mortality as a proxy for all types of opioid-related harms and otherwise uses unreliable data to measure opioid-related harms;[10] and
- There is a "critical mismatch" between Professor Rosenthal's analysis based on prescription data and my analysis based on shipments data.[11]

3. This declaration addresses each of these claims and does not address issues not raised in defendants' Daubert motion. My failure to address any other specific argument by defendants in their Daubert motion should not be interpreted to mean that I find it to be legitimate, and I expressly reserve the right to respond to other issues raised by defendants through their expert reports. This declaration shows that in each case defendants either misunderstand or mischaracterize my analysis, or that their arguments are not supported by available data, including the data I utilized for my Report. None of the arguments made in defendants' motion (or by defendants' experts) leads me to revise the opinions or conclusions expressed in my March 25 Report. To the contrary, they strengthen the opinions and conclusions I reached in my Report.

4. Before addressing defendants' specific arguments, it is important to recognize that my analysis applies a variety of tools of economic analysis to evaluate the impact of shipments of prescription opioids on harms that impose costs on Bellwether governments. Each of these tools is standard and widely used among economists, including: (i) regression analysis that directly evaluates the relationship between shipments of prescription opioids and opioid-related mortality; (ii) regression analysis that indirectly estimates the impact of shipments of prescription opioids on mortality as a residual after controlling for other possible explanatory factors; and (iii) analysis of benchmark metrics

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[8] Defendants' Daubert Motion, p. 11.
[9] Defendants' Daubert Motion, p. 12.
[10] Defendants' Daubert Motion, p. 15.
[11] Defendants' Daubert Motion, p. 16.

previously applied in the economic literature to measure opioid-related harms. Defendants and their experts do not propose alternative analytical frameworks for evaluating these relationships and do not establish that my analysis is unreliable or overstates the impact of defendants' misconduct.

5. To the contrary, defendants' experts attempt to critique my analysis only by modifying the regression models I have implemented. For example, defendants and their experts argue that additional variables should be added to my regression analyses or propose alternative ways to measure variables included in my regression analyses. Notably, while defendants argue that my analysis is unreliable, none of defendants' experts dispute a central conclusion of my initial report – that opioid-related harms faced by Bellwether jurisdictions have a significant statistical relationship to shipments of prescription opioids. The one exception to this claim, which appears to underlie a key argument in Defendants' Daubert Motion, is based on a basic error made by defendant's expert. This error is explained in more detail below.

6. As documented in this declaration and set forth in my March 25 Report, my key conclusions are as follows:

- Defendants' argument that my opinions "do not 'fit' the case" reflects a misunderstanding or mischaracterization of my analysis. The framework presented in my March 25 Report can be used to distinguish harms from lawful and unlawful shipments; harms from shipments by defendants and non-defendants; and harms from illicit and prescription opioids. This conclusion, which is clearly spelled out in my Report, is discussed in Section II below.

- Defendants' argument that my opinions are based in part on an inappropriate national regression model reflects a misunderstanding of the how the statistical analysis I utilized in March 25 Report is used to estimate the relationship between shipments of opioids and opioid-related mortality. Section III below explains that my analysis is based on standard economic and statistical methodologies with previously identified strengths and limitations that yield a modest and credible range of results.

- There is no basis to defendants' claim that my statistical analyses omit key variables that render it unreliable. I show that claims by defendants and their experts that my analysis fails to adequately account for "deaths of despair" are based on a flawed interpretation of available data or outright errors in their analysis. This analysis is presented in Section IV below.

- Defendants' claim that my conclusions are based on an "unsupported theory" that the post-2010 increase in illicit opioid harms was the result of defendants' prior misconduct reflects a misrepresentation or misunderstanding of the analysis presented in my Report. Defendants' arguments are also contradicted by the analysis presented by Professor Jonathan Gruber in his Expert Report, as well as economic and epidemiological studies analyzing the increase in illicit opioid harms. This issue is discussed in Section V below.

- Defendants' claim that my analysis inappropriately uses mortality as a proxy for all types of opioid-related harms ignores, among other things, the supporting analysis presented in my March 25 Report that relates shipments of prescription opioids and crime. As set forth in my Report, that analysis establishes that my approach, if anything, likely understates the magnitude of many categories of opioid-related harms. In addition, my analysis of opioid-related harms faced by the Bellwether governments is based on the best available data. This analysis is addressed in Section VI below.

- Finally, there is no basis to defendants' claim that my analysis is unreliable because there is a "critical mismatch" between Professor Meredith Rosenthal's analysis based on prescription data and my analysis based on shipments data. As set forth in my Report and discussed in Section VII below, the analysis that is the basis of this claim is based on inappropriate data with obvious irregularities and is contradicted by alternative sources of prescription data.

II. Defendants' claim that my opinions do not "fit" plaintiffs' theory of the case mischaracterizes my analyses and opinions.

7. Defendants argue that my opinions "do not 'fit' Plaintiff's theory of the case" and "are not tied to Plaintiffs' burden of proof."[12] They claim that my analysis fails to distinguish harms from: (i) lawful vs. unlawful shipments; (ii) shipments by any particular defendants; and (iii) illicit and prescription opioids.[13]

8. This section shows that defendants misunderstand or mischaracterize my analyses and opinions. As described in my March 25 Report at ¶ 23, my analysis estimates the share of harms attributable to defendants' misconduct in three steps:

$$\begin{aligned} &\mathit{Share\ of\ Harm\ Attributable\ to\ Defendants'\ Misconduct} \\ &\quad = \mathit{Share\ of\ Harms\ Attributable\ to\ Opioids} \\ &\qquad x\ \mathit{Share\ of\ Opioid\ Harms\ Attributable\ to\ Opioid\ Shipments} \\ &\qquad x\ \mathit{Share\ of\ Opioid\ Shipments\ Due\ to\ Defendants'\ Misconduct} \end{aligned}$$

[12] Defendants' Daubert Motion, p. 3-4.
[13] Defendants' Daubert Motion, p. 4-5.

9. I first estimate the share of harms faced by Bellwether governments attributable to all opioids. I then estimate the share of opioid-related harms attributable to shipments of prescription opioids using both direct and indirect regression analyses of the relationship between shipments and opioid-related mortality.[14] In order to estimate harms attributable to defendant misconduct, I incorporate estimates of the share of prescription opioid shipments that are attributable to manufacturer misconduct from Professor Rosenthal and estimates of the share of prescription opioid shipments attributable to distributor misconduct from Dr. Craig McCann.[15] As this indicates, my analysis plainly distinguishes harm from lawful and unlawful shipments, as well as shipments from defendants and non-defendants. Defendants' claims to the contrary reflect a misunderstanding or mischaracterization of my analysis.

10. Defendants' claim that my analysis fails "to attribute any 'harms' in the Track 1 Counties to any particular Defendant"[16] also reflects a misunderstanding or mischaracterization of my analysis. As noted in my March 25 Report, my analysis together with those of Professor Rosenthal and Dr. McCann can be applied on a directly on defendant-specific basis to estimate the relative contribution to damages of individual manufacturers and distributors.[17]

[14] Cutler Report, Section V.

[15] The updated estimates are reported in the Supplemental Expert Report of Craig J. McCann, April 3, 2019, which was submitted after my March 25 Report. Appendix III.J of my March 25 Report set forth results based on preliminary estimates of the percent of shipments attributable to distributor misconduct. These estimates have been updated. **Appendix A** to this declaration updates Appendix Tables III.J.1-5 based on these updated estimates.

[16] Defendants' Daubert Motion, p. 4.

[17] Cutler Report, footnote 75. Appendix III.J of my March 25 report also noted that opioid-related harms could have been avoided by actions of either manufacturers or other CSA registrants. The approach outlined in my March 25 report can be applied directly on a defendant-specific basis given any attribution of aggregate harm across these categories of defendants. Any reduction from the average estimated effect for one defendant would need to be offset by an increase to others to preserve the average and to maintain the appropriate aggregate damage award.

11. Finally, defendants argue that my analysis of the relationship between opioid shipments and mortality fails to account for the effects of "different types of prescription opioids," "the reason why an opioid was prescribed", and the "length of the prescription."[18] However, available mortality data do not identify the specific opioid associated with an opioid-related death. For example, the mortality data for the period 1993-1998 allow identification of mortality due to opioids, but do not distinguish the specific type of opioid involved. Starting in 1999, available mortality data distinguish between prescription opioids, heroin and synthetic opioids but these data do not identify the type of prescription opioids involved and also do not distinguish between deaths from licit and illicit fentanyl.

12. The lack of availability of mortality data that can be used to address these particular effects does not imply that my analysis of the overall relationship between shipments (measured in MMEs) and opioid-related mortality is economically unreliable. None of the defendant experts commenting on my report has proposed or identified an alternative source of data or an alternative analytical framework that can be used to evaluate the impact of "different types" of opioids, the "reasons" for a prescription and the "length" of the prescription.

III. There is no basis to defendants' claim that my "aggregate" analyses are "impermissible and irrelevant".

13. Defendants argue that my analyses address only the "alleged aggregate impact of all shipments […] on mortality across the nation" and do not "assess the impact of any actual shipment […] on mortality in Track One Counties".[19] Defendants also argue that my analysis has a high "error rate."[20] This section shows that defendants' arguments again reflect a misunderstanding or mischaracterization of my analysis and, more generally, the nature of statistical analysis.

[18] Defendants' Daubert Motion, p. 6.
[19] Defendants' Daubert Motion, p. 7.
[20] Defendants' Daubert Motion, p. 10.

A. The "aggregate" regression methodologies I utilize are reliable.

14. The regression models presented in my initial report are applications of standard econometric tools that are commonly used to estimate the relationship between economic variables based on comparisons across different geographic regions. As explained in my March 25 Report, my direct regression model is a form of "long difference" analysis which is widely used by economists to analyze the determinants of long-term changes in economic outcomes.[21] For example, my approach is similar to that used by Professor Christopher Ruhm to analyze the effect of changes in economic conditions on opioid-related mortality.[22] I have previously used this methodology in my own peer-reviewed research on changes in rates of youth suicide and in the value of medical improvements over time.[23] Other economists have used this approach to analyze topics such as the impact of expanded trade with China on employment and the effect of crime on property values.[24]

15. The indirect regression models presented in my initial report are also applications of standard techniques used in the economic literature. Indirect regressions are forms of "residual analysis" that estimate the relationship between mortality and a set of demographic and economic variables in a base period prior to the misconduct of defendants. Based on those relationships, the approach predicts changes in the level of opioid-related mortality expected in the absence of misconduct. I have previously used this indirect approach in my own peer reviewed research, including

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[21] Cutler Report, ¶ 84.

[22] Ruhm, Christopher J. "Deaths of Despair or Drug Problems?" NBER Working Paper 24188 (January 2018).

[23] Cutler, David M., Edward L. Glaeser and Karen E. Norberg. "Explaining the Rise in Youth Suicide," in Jonathan Gruber, ed., *Risky Behavior Among Youths: An Economic Analysis*, Chicago: University of Chicago Press, 2001: 219-269 (Cutler et al (2001)); Cutler, David M., Allison B. Rosen and Sandeep Vijan. "Value of Medical Innovation in the United States: 1960-2000." *New England Journal of Medicine* 355:(2006): 920-927.

[24] Autor, David H., David Dorn, and Gordon H. Hanson. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (2013): 2121–2168; Autor, David H., David Dorn, and Gordon H. Hanson. "The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade." *Annual Review of Economics* 8 (October 2016): 205-220; Devin G. Pope and Jaren C. Pope. "Crime and Property Values: Evidence from the 1990s Crime Drop." *Regional Science and Urban Economics* 42 (2012): 177-188.

my study examining price indices for heart attack treatment.[25] Analysis of residual differences are commonly used to analyze discrimination-related issues such as racial and/or gender differences in earnings that cannot be explained by measured economic and demographic characteristics. As discussed in my March 25 Report, residual analysis is also commonly used to estimate the impact of technological change in output, which is typically measured as growth in output that is not explained by the growth in inputs.[26]

16. Defendants erroneously claim that this approach "assume[s its] way to an opinion of causation."[27] This statement is incorrect. To the contrary, my indirect regression analyses establish that the increase in opioid mortality cannot be explained by a broad set of economic and demographic variables I reviewed and utilized in my March 25 Report. The increase in mortality occurs at a time of rapidly increasing shipments of prescription opioids. As explained further below, defendants and their experts fail to provide a credible alternative explanation for the increase in opioid mortality over this period other than the large growth in shipments of prescription opioids.

17. As discussed in my March 25 Report, my direct regression model likely understates the true relationship between shipments of prescription opioids and opioid-related mortality.[28] This is because the analysis of the impact of defendants' actions ideally would relate the consumption of opioids in an area to opioid-related mortality in the area. Because data on consumption in an area are not available, data on shipments of prescription opioids to an area are used as an approximation. However, this approximation is not perfect due to the potential for diversion of shipments to illicit distribution channels resulting in consumption in other areas. It is well recognized that measurement

[25] Cutler David M., Mark McClellan, Joseph P. Newhouse and Dahlia Remler. "Are Medical Prices Declining? Evidence from Heart Attack Treatments," *Quarterly Journal of Economics* 113(4) (November 1998): 991-1024.
[26] Cutler Report, ¶ 80 (citing Firpo S, Lemieux T, Fortin N. "Decomposition Methods in Economics." In D. Card and O. Ashenfelter, eds., *Handbook of Labor Economics*, 4th Edition, North Holland: Elsevier (2011):1-102.)
[27] Defendants' Daubert Motion, p. 5.
[28] Cutler Report, ¶ 68.

error of this type will reduce the estimated relationship between shipments and opioid-related mortality relative to the true value.[29] Thus, my direct model is likely to yield an underestimate of the relationship between shipments and opioid-related mortality. At the same time, the indirect approach attributes any increases in mortality not explained by changes in economic and demographic factors to shipments and, as noted in my Report, has the potential to overstate the impact of shipments on opioid-related mortality.[30] But the indirect approach is not certain to overstate the relationship between and opioid-related harms. For example, the increased use of naloxone in recent years reduces deaths but not necessarily other opioid-related harms. As a result, the indirect model may also understate the relationship between shipments and certain opioid-related harms and thus lower damage estimates.

18. Taken together, my two alternative approaches yield a range of results based on standard economic methodologies. **Table 1** below summarizes the range of results from both approaches from 2006-2016 as reported in my March 25 Report and indicates that that between 65 percent and 85 percent of opioid mortality over the 2006-16 period is attributable to shipments of prescription opioids. Consistent with the discussion above, Approach 1 which relies on the direct regression generates lower percentages than Approach 2 which relies on the indirect regression.

[29] J. Wooldridge, *Econometric Analysis of Cross Section and Panel Data,* 2nd ed. (2010), pp. 78-82.
[30] Cutler Report, ¶ 78 and footnote 53.

Table 1

Impact of Shipments on Opioid Mortality
2006-2016

Year	Approach 1 (Direct Model)	Approach 2 (Indirect Model)
2006	49%	84%
2007	50%	86%
2008	51%	85%
2009	52%	77%
2010	55%	78%
2011	58%	82%
2012	67%	84%
2013	74%	86%
2014	81%	89%
2015	87%	91%
2016	91%	93%
Avg.	65%	85%

19. The two analytical approaches I use to evaluate the relationship between shipments of prescription opioids are standard econometric techniques that yield a reasonable range of results that are consistent with the known limitations of available data. Indeed, defendants' own experts rely on similar methodologies in their analysis. There is simply no basis to defendants' claim that these approaches yield unreliable results.

B. Estimate of the "average" impact of shipments on mortality are reliable and do not inflate damage estimates.

20. Defendants further suggest that my calculation that attributes opioid mortality to shipments are inappropriately based on estimates of average shipments instead of estimates specific to the Bellwether counties. As explained in my deposition and in my Report, the most appropriate way to interpret the results of my regression analyses is to determine the impact of shipments on mortality based on results for the sample of large counties, which reduces the potential for measurement errors

specific to any geographic area to distort impact estimates.[31] This is what I have presented in my March 25 Report, which uses the regressions to estimate the impact of shipments on average from 2006-2016.

21. While the results presented in my March 25 Report are economically appropriate and reliable for the reasons mentioned herein and consistent with the assignment given to me in this case, it is also possible to estimate the impact of shipments on opioid mortality based on data specific to each of the two Bellwether counties using the same methodology I utilized in my March 25 Report. **Table 2** summarizes the results of applying my analyses to the Bellwether counties based on county-specific shipments and mortality data.

Table 2

Impact of Shipments on Opioid Mortality, Average vs. Bellwether Counties
2006-2016

	Approach 1			Approach 2		
Year	**Average**	**Cuyahoga**	**Summit**	**Average**	**Cuyahoga**	**Summit**
2006	49%	36%	57%	84%	88%	89%
2007	50%	47%	49%	86%	85%	92%
2008	51%	39%	68%	85%	87%	89%
2009	52%	51%	84%	77%	78%	79%
2010	55%	35%	51%	78%	87%	87%
2011	58%	38%	55%	82%	92%	87%
2012	67%	63%	67%	84%	93%	93%
2013	74%	66%	87%	86%	93%	92%
2014	81%	73%	89%	89%	94%	96%
2015	87%	76%	91%	91%	95%	97%
2016	91%	88%	85%	93%	97%	98%
06-16 Avg.	65%	56%	71%	85%	90%	91%

22. As **Table 2** demonstrates, these alternative calculations are *very similar* to those based on the approach presented in my March 25 Report. For Approach 1, which relies on the direct regression, the impact of shipments on mortality based on county-specific data is slightly higher in

[31] Deposition of David Cutler, April 27, 2019, pp. 526:9 – 529:16; *see also:* Cutler Report, ¶ 90.

Summit County and slightly lower in Cuyahoga County than those based on the average approach. For Approach 2, which relies on the indirect regression, the impact of shipments based on county-specific data is slightly higher in both counties than the estimate based on the average.

23. Further, the variability inherent in applying the regression parameters to specific counties is evidenced by the noisier trend in impact percentage estimates for the counties taken individually, relative to the average. For this reason, the average is generally preferred by researchers over an analysis specific to a single area. The potential for area-specific measurement errors to distort the interpretation of an econometric analysis is further highlighted in evaluation of the results of one of the Defendant's expert's (Professor Margaret Kyle) analysis presented in Section VII below.

24. As a result, there is no basis to defendants' claim that the results presented in my Report based on the "averaging" approach are unreliable or somehow overstate the impact of shipments of prescription opioids on opioid mortality.

C. There is no basis to defendants' claim that my analysis has a high "error rate"

25. Defendants, citing to the expert report of one of their experts, Professor Kevin Murphy, also argue that my analysis is unreliable because some counties with higher than average shipments have lower than average mortality (and vice versa).[32] They suggest based on this observation that this implies that my analysis has a high "error rate."[33] However, this criticism ignores the fact that my analysis controls for a wide variety of other factors which affect mortality. My analyses do not presume that shipments are the only factor which affects mortality but instead demonstrate that even after accounting for a large set of county-specific factors (such as levels and changes in employment rates, age and gender demographics, and education), there is a large and significant relationship between the

[32] Defendants' Daubert Motion, p. 10.
[33] *Id*.

shipments of opioids in a county and the opioid-related mortality rate in that county. In contrast, Professor Murphy does not consider any such factors in making this observation.[34]

26. The suggestion by defendants that my analysis has a high "error rate" or is otherwise unreliable as a result is simply incorrect. My analysis establishes a large and statistically significant relationship between shipments and mortality. Further, as I noted in my report and in my deposition, the regression has a very high goodness of fit (R^2 metric), especially for a cross-section regression.[35] The fact that mortality for a given county deviates from the regression-based prediction does not alter those facts.

27. Finally, my regressions and my analyses do not assume that areas with lower than average shipments were somehow unharmed. As Professor Gruber showed in his report, there is an increase in shipments and opioid-related mortality in nearly all counties analyzed.[36] The harms associated with defendants' misconduct are also expected to occur in low-shipments counties, albeit at a lower level than in the counties with relatively more shipments.

IV. Defendants' claim that my analysis is unreliable because it omits key variables is based on a misinterpretation of available data and is not supported by available evidence

28. Defendants claim that both my direct and indirect models of the relationship between shipments of prescription opioids and opioid-related mortality "failed to include control variables […] reflecting 'deaths of despair' that have been widely studied in the economic literature."[37] Defendants' Daubert Motion cites their experts' claim that inclusion of measures of non-opioid deaths of despair in my regression models reduce or eliminate the estimated relationship between shipments and opioid mortality.[38] In their view, shipments of prescription opioids are correlated with a variety of measures of

[34] Corrected and Restated Expert Report of Kevin M. Murphy, Ph.D., June 21, 2019, ("Murphy Report), ¶ 115.
[35] Cutler Deposition Tr. 682:18-685:3.
[36] Expert Report of Professor Jonathan Gruber, March 25, 2019, (the "Gruber Report"), ¶ 73.
[37] Defendants' Daubert Motion, p. 13.
[38] Defendants' Daubert Motion, p. 14.

deaths of despair so the estimated relationship between shipments and opioid mortality reflects a wider set of economic and social conditions forces that affect opioid mortality.[39]

29. This section reviews first trends in non-opioid deaths of despair and their relationship to shipments of prescription opioids and then evaluates the impact of certain measures of deaths of despair on estimates of the relationship between opioid mortality and shipments of prescription opioids. The analysis confirms that my regression models are appropriately specified and that my estimates of the relationship between opioid mortality and shipments are not inflated due to omission of certain variables. The analysis further establishes that defendants' experts' claims to the contrary are driven in substantial part by fundamental errors in data analysis that they make.

A. Omitted variables do not inflate direct estimates of the relationship between shipments and opioid-related mortality

30. Deaths of despair, as defined by Case and Deaton, are a composite of multiple types of mortality: drug-related overdose deaths, suicides, and alcohol-related liver disease.[40] Figure 1 summarizes trends in opioid-related mortality as well as the three categories of deaths of despair from 1993-2016 based on data from the CDC. The opioid mortality rate reported incorporates the Ruhm adjustment described in my initial report.[41] For reasons described below, data on non-opioid drug overdoses are based on those with identified causes (e.g., cocaine or methamphetemines) and exclude unclassified drug overdoses.

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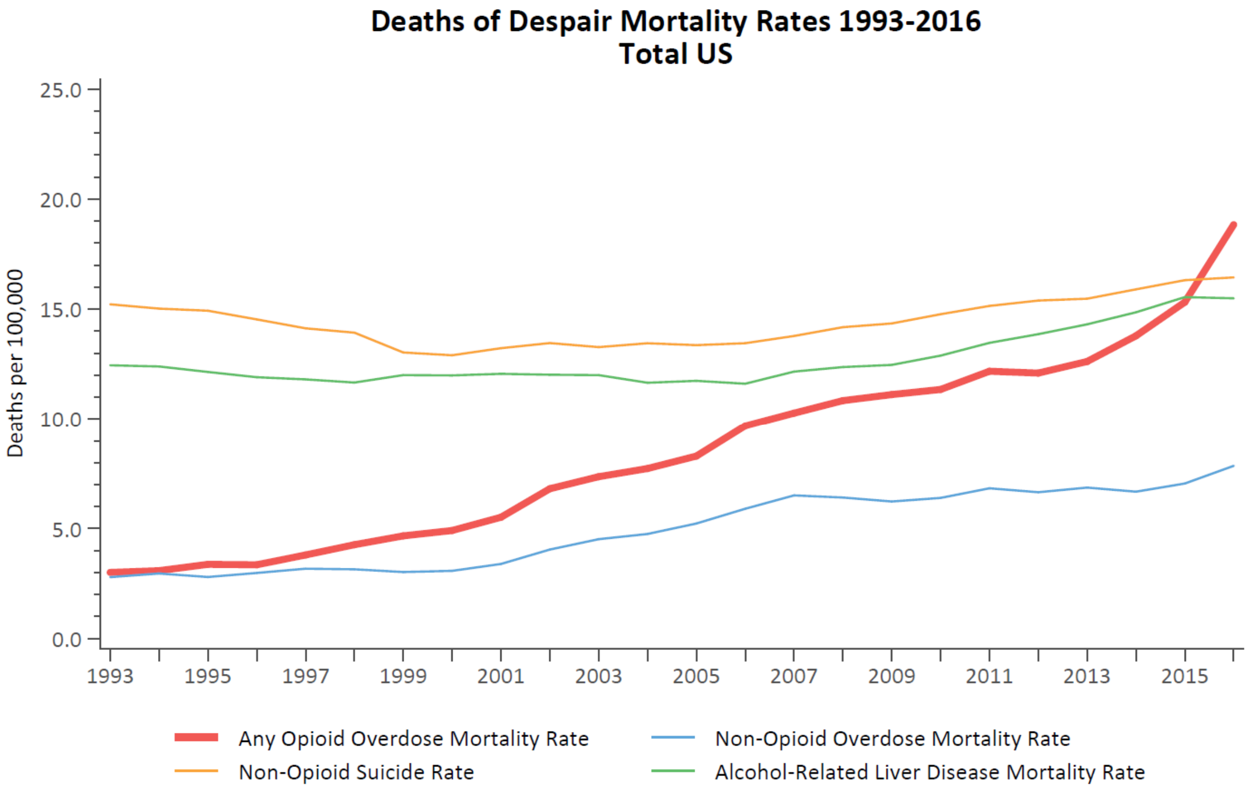
[39] Murphy Report, ¶¶ 132-136.

[40] Anne Case & Angus Deaton, "Mortality and Morbidity in the 21st Century," *Brookings Papers on Economic Activity*, Spring 2017, pp. 397-476, at p. 398.

[41] As discussed in my opening report, the Ruhm adjustment is used to allocate to opioids a portion of overdose deaths for which a specific drug is not identified. Briefly summarized, this allocation is based on the share of overdoses with identified drugs that are attributable to opioids as well as the demographic profile of opioid overdoses. The analysis presented below defines non-opioid drug overdoses excluding those attributed to opioids as the result of the Ruhm procedure.

Figure 1



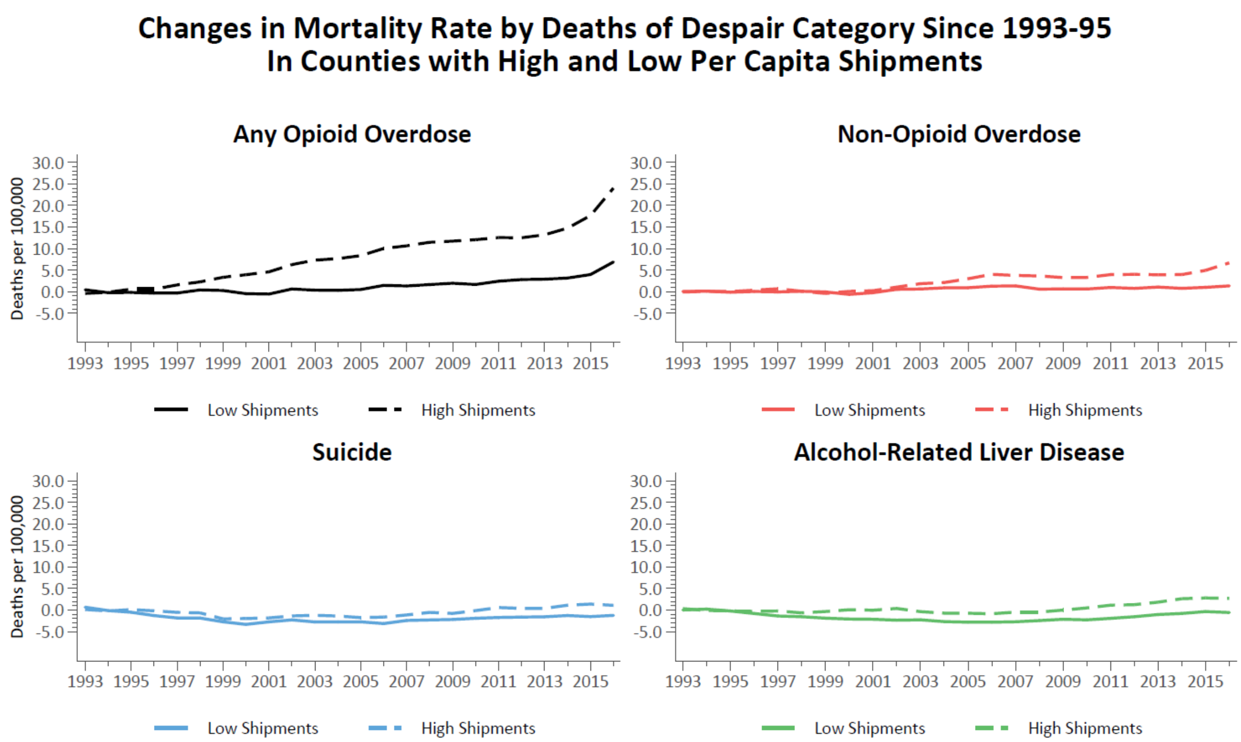
Source: CDC.

31. As **Figure 1** demonstrates, opioid mortality (represented by the bold red line) grew rapidly over this entire period, while mortality from suicides and alcohol-related liver disease fell between 1993 and 2005, and then grew slowly from 2005 to 2016. Non-opioid overdose mortality (depicted by the blue line) started to grow after 2001, several years after the increase in opioid-related mortality and then leveled off in 2007.

32. These patterns indicate that opioid-related mortality does not simply reflect the same set of forces that drive trends in other deaths of despair categories. The fact that increases in non-opioid overdoses, suicide, and liver disease mortality are not observed until *after* the opioid crisis was well under way raises a possibility that they are, at least in part, a *consequence* of the opioid crisis, not the simple product of a common set of factors that that drive trends in opioid mortality.

33. **Figure 2** demonstrates graphically that shipments of prescription opioids are only weakly related to non-opioid deaths of despair. This figure reports mortality rates for counties in the large county sample in the top and bottom 25 percent of counties based on per capita opioid shipments from 1997-2010. As demonstrated in the top left quadrant, opioid mortality grew more rapidly in high-shipment counties relative to low-shipment counties. For non-opioid deaths of despair, however, the differences in these trends between high and low shipment counties are small with no material trend or even declines observed in low shipment counties.

Figure 2



Source: CDC.
Notes: [1] Excludes counties with greater than 3.5 MME per capita per day from 1997-2010.
[2] Low and high shipment categories include counties in the bottom and top 25% of 1997-2010 shipments per capita, respectively.

34. Statistical analysis of the trends reported in **Figure 2** establishes that while mortality grew more rapidly in high shipment counties relative to low shipment counties for each category, the "growth gap" between high and low shipment counties was significantly greater for opioid-related

mortality compared to other categories.[42] For example, between 1995 and 2016, the opioid-related mortality increased by 24.0 per 100,000 in high shipment counties compared to an increase of 6.9 per 100,000 in low shipment areas, a difference of 17.2 per 100,000. Over the same period, this growth gap was substantially lower for other categories of deaths of despair: 2.3 per 100,000 for suicide, 3.3 per 100,000 for alcohol-related liver disease, and 5.4 per 100,000 for non-opioid overdose mortality.

35. Because drug overdoses are more likely to be driven by similar factors than are alcohol and suicide, and because the gap in mortality growth between high and low shipment areas is greater among non-opioid overdoses compared to suicides or alcohol-related liver disease, I focus on non-opioid drug overdoses in testing defendants' "omitted variable" claim. To the extent that shipments of prescription opioids in an area are a proxy for a broader set of conditions that drive all types of health-harming behavior, then inclusion in my regression analysis of a variable measuring non-opioid overdoses in an area would be expected to result in a material reduction in the estimated relationship between shipments and opioid mortality.

36. This is not true empirically. **Table 3** shows that the estimated relationship between shipments and opioid mortality is only marginally affected by including non-opioid drug overdose mortality rates specific to different types of non-opioid drugs as independent variables in the regression analysis.[43] This result holds when non-opioid overdose rates with identified causes enter the regression

[42] The statistical significance of the difference in the "growth gap" for different death of despair categories was evaluated by estimating the difference in mortality trends in high and low shipment for each category, and then statistically testing whether this difference for opioid mortality is different from that estimated for the other categories. Each of these differences are highly significant and would be observed by chance with probability less than 0.1 percent.

[43] These estimates are based on data starting in 1999 because mortality rates specific to these drugs are not available before that time.

analysis together or separately. These results reflect the fact that shipments of prescription opioids are not highly correlated with non-opioid overdose mortality.[44]

Table 3

Estimated Relationship Between Shipments and Mortality With Non-Opioid Drug Mortality as Additional Controls

Scenario	Additional Control Variable	Shipment Coefficient	P-Value
1	Base Result	3.59	0.000
2	All Non-Opioid Overdose Mortality Rate	3.32	0.000
3	Cocaine Overdose Mortality Rate	3.58	0.000
4	Benzodiazepine Overdose Mortality Rate	3.49	0.000
5	Methamphetamine Overdose Mortality Rate	3.58	0.000
6	Other Non-Opioid Overdose Mortality Rate	3.53	0.000
7	Unclassified Non-Opioid Overdose Mortality Rate	2.63	0.000

Note: Based on large county sample. Dependent variable is change in opioid mortality rate from 1999-2000 to 2009-2010.

37. An exception to the results reported in **Table 3** is the inclusion in the regression of a measure of unclassified non-opioid overdoses, which is reported as Scenario 7 above. Unclassified non-opioid overdoses are those for which no drug is reported. The inclusion of this variable in the regression analysis reduces the shipment coefficient from 3.59 to 2.63. This result indicates that shipments of prescription opioids are correlated with unclassified drug overdose deaths.

38. This finding demonstrates that counties with high unclassified drug overdose rates tend to have relatively high shares of opioid-related overdoses, which almost certainly are incorrectly

[44] These results are consistent with the economic literature, which has similarly found that trends in opioid-related mortality are inconsistent with trends in other drug-related overdose mortality including cocaine. For example, Alpert, Powell, and Pacula (2018) applied their analysis to cocaine mortality and to all non-opioid drug mortality. They conclude: "We find little evidence of effects for other drugs. Other drugs may be complements or substitutes for opioids so it is not clear whether we would expect to observe any relationship, but the statistical absence of any effect is reassuring that the heroin effect is not driven by concurrent demand shocks for drugs more generally." Abby Alpert, David Powell and Rosalie Liccardo Pacula, "Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids," American Economic Journal: Economic Policy 2018 10 (2018): 1-35, at p. 30.

included in the "unclassified" category. As noted in my initial report, some unclassified drug poisoning deaths are allocated to opioids using the procedure developed Christopher Ruhm. Briefly described, that procedure allocates unclassified drug overdoses to opioids and non-opioids in approximate proportion to opioids' share of classified drug overdoses.[45] However, any error in the reallocation of deaths at the county level will leave some opioid deaths remaining in the unclassified death category. If counties with more deaths due to opioids also have more opioid deaths that are not classified to a specific cause, the result will be a spurious correlation between opioid-related deaths and unclassified drug overdose death at the county level.[46] Professor Ruhm acknowledges that the adjustment he developed may be imperfect.[47]

39. Defendants' expert Professor Murphy does not consider the possibility that unclassified drug overdoses include opioid-related overdoses in his analysis and that his results are distorted by this fact. In both his "Method 1" and "Method 2" approaches to measuring non-opioid mortality, Professor Murphy includes all non-opioid deaths of despair as explanatory variables, including unclassified drug overdoses. Inclusion of a measure of "non-opioid deaths of despair" that includes opioid-related mortality necessarily, and improperly, reduces the role of shipments of prescription opioids in explaining mortality. Of note, even with this possibility, Professor Murphy still estimates a strong relationship between shipments and opioid-related mortality.

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[45] Ruhm, Christopher J., "Geographic Variation in Opioid and Heroin Involved Drug Poisoning Mortality Rates." American Journal of Preventive Medicine 53, No. 6 (2017): 745-753 ("Ruhm (2017)"); Ruhm, Christopher J., "Corrected US opioid involved drug poisoning deaths and mortality rates, 1999–2015," Addiction 113 (2018): 1339-1344. The adjustment is done in the framework of a logit model which predicts the probability that a classified overdose death is opioid related based on demographic control variables.

[46] If areas with relatively higher opioid overdose rates have relatively higher shares of unclassified overdoses with (misclassified) opioid doses, then the Ruhm adjustment will systematically understate the true difference in opioid overdose rates across areas. As a result, estimates of the true relationship between shipments and opioid overdose rates will be greater than that estimated, even after application of the Ruhm adjustment.

[47] Ruhm (2017), p. 752: "[T]he imputations assume that data on the drugs involved in overdose deaths were 'missing at random,' meaning that the probability of a missing value varies only with the characteristics controlled for in the imputation process."

40. In addition, Professor Murphy's "Method 1" approach makes a more fundamental statistical error. In that method, Professor Murphy includes deaths explicitly identified as opioid-related in his measure of "non-opioid deaths of despair." The approach results in an even greater bias in the estimated relationship between shipments and opioid mortality. To explain, the CDC data used by experts in this case to identify opioid-related deaths – including defense experts Professors Kyle and Iain Cockburn and others – report both an "underlying cause of death" code as well as an additional set of distinct codes for "multiple causes of death." In order to identify opioid-related deaths, it is necessary to review the "multiple causes of death" codes reported in the CDC data for a given death as well the "underlying cause of death" codes, which by themselves do not fully identify drugs involved in an overdose. Professor Murphy's Method 1 fails to consider opioid-related deaths identified through the "multiple causes of death" codes when constructing a measure of non-opioid deaths of despair. This is completely inconsistent with the standard and widely used approach to identifying opioid-related mortality.[48]

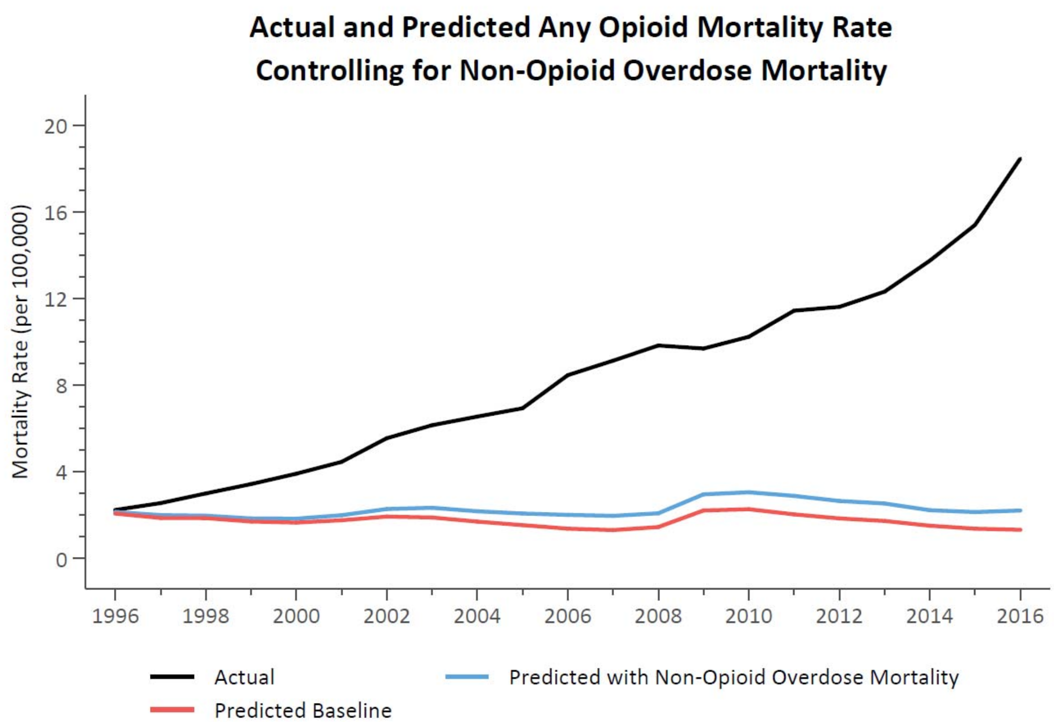
41. Professor Murphy's "Method 1" analysis is the only regression specification presented by any of defendants' expert that suggests that there is not a statistically significant relationship between shipments and opioid mortality. Thus, there is no basis for defendants claim that analysis by defendants' experts "dramatically reduced or even eliminated" the estimated relationship between shipments and opioid mortality.[49]

[48] For example, the CDC explains its method for identifying opioid-related overdose deaths in: CDC National Center for Injury Prevention and Control, "2018 Annual Surveillance Report of Drug-Related Risks and Outcomes," p. 39. See, also: Ruhm (2017), at 746.
[49] Defendants' Daubert Motion, p. 14.

B. Omitted variables do not inflate indirect estimates of the relationship between shipments and opioid-mortality

42. Defendants' also argue that the results of my indirect regression analyses are distorted because I did not include variables that reflect deaths of despair.[50] As an empirical matter, this critique is not accurate. **Figure 3** summarizes the results from an alternative indirect regression that includes mortality rates for non-opioid drug overdoses as an additional explanatory variable. The blue line in the figure shows the revised predicted mortality rates after including non-opioid overdose deaths with a specified drug in the indirect regression. As shown in **Figure 3**, the revised predictions of opioid mortality are not materially different from the original results, which are depicted in red.

Figure 3



Source: NCHS Mortality data and US Census data

[50] Defendant's Daubert Motion, p. 13.

V. There is no basis to defendants' claim that my attribution of increased harms from illicit opioids to earlier shipments of prescription opioids reflects an "unsupported theory."

A. Defendants ignore analysis establishing that the post-2010 illicit opioid crisis was the consequence of the prescription opioid crisis

43. Defendants' claim that my conclusion that defendants are responsible for the post-2010 increase in illicit opioid mortality is based on an "unsupported theory" of a "made up 'thickening' of the illegal drug market" reflects a misunderstanding or misrepresentation of my analysis.[51] My analyses and those of Professor Gruber carefully analyze the relationship between shipments of prescription opioids before 2010 and the growth of illicit mortality after 2010.

44. As indicated by my Report, Professor Gruber's Report, and related research literature including economic and epidemiological studies cites in both reports, the high level of shipments of prescription opioids prior to 2010 created a large pool of individuals dependent on opioids. Starting in 2010, the supply of prescription opioids available to meet addicts' needs started to become restricted. A variety of factors contributed to this decline including, among others: OxyContin was reformulated in order to make it more difficult to abuse; medical organizations began warning about excessive prescribing of opioids; federal and state governments expanded enforcement against pill mills; and states began to implement Prescription Drug Management Programs in order to reduce excessive prescriptions and to prevent "doctor shopping" by those dependent on opioids.[52]

45. These events created an increased demand for illicit opioids among individuals that had become dependent as the consequence of prescription opioids shipments. That increased demand then induced an increase in the supply (and abuse) of illicit opioids after 2010 – the thickening of the illicit opioid market documented by Professor Gruber and myself. The analyses presented in my March 25 Report establish that:

[51] Defendants' Daubert Motion, p. 12.
[52] Gruber Report, pp. 24-28.

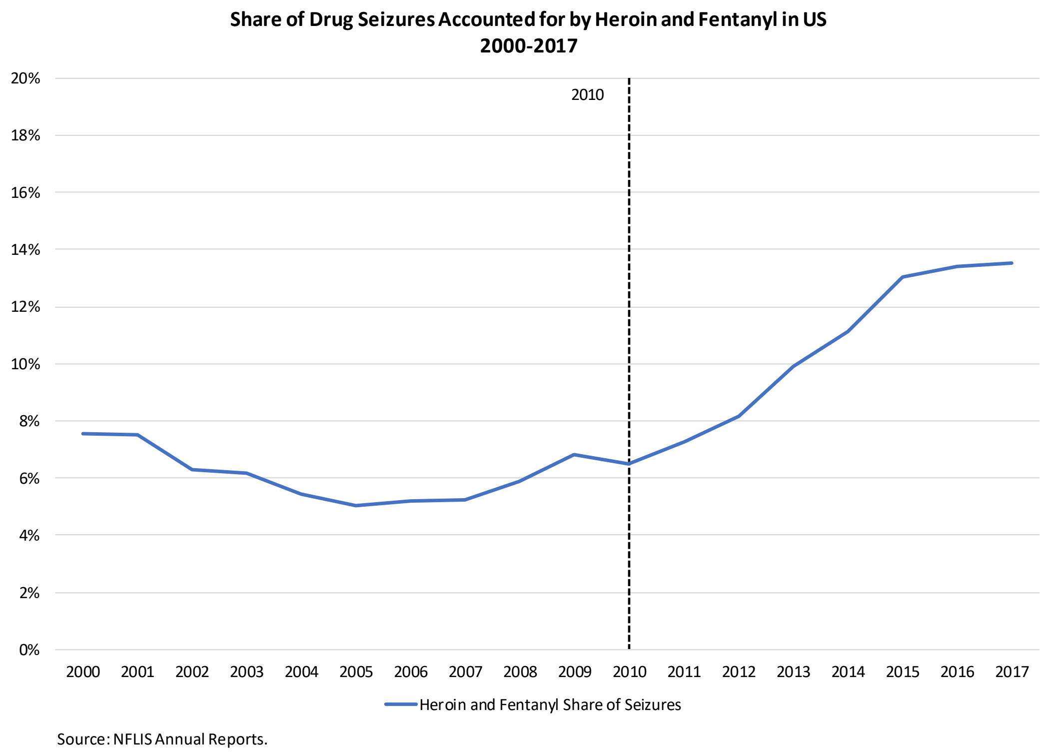
- There was a statistically significant "structural break" in heroin mortality trends resulting in much more rapid growth starting in late 2010, roughly coincident with the reformulation of OxyContin and related market events mentioned above. At the same time there was a statistically significant structural break resulting in a decline in prescription opioid mortality.[53] This analysis was not challenged by any of defendants' experts.
- A separate structural break analysis establishes that the heroin mortality rate accelerated significantly more rapidly in counties that received high per capita shipments of prescription opioids in 1997-2010 compared to those that received lower per capita shipments. This analysis establishes a direct statistical link between increases in illicit opioid mortality and prior shipments of prescription opioids. This analysis was not challenged by any of defendants' experts.[54]
- Professor Gruber also shows that illicit opioid mortality (involving heroin or fentanyl) grew far more rapidly in counties that received higher per capita shipments of prescription opioids compared to those that received lower per capita shipments after 2010.[55]
- Professor Gruber further establishes that fentanyl mortality emerged after 2013 most strongly in counties that had experienced large increases in heroin mortality between 2010-13. He establishes that the correlation between county-level fentanyl mortality in 2016 and the increase in heroin mortality in 2010-13 is large and statistically significant.[56]

[53] Cutler Report, pp. 29-34.
[54] Cutler Report, p. 35.
[55] Gruber Report, p. 60.
[56] Gruber Report, p. 41.

- Both Professor Gruber and I cite epidemiological studies that further establish that many individuals getting treatment for heroin addiction first started using prescription opioids.[57]
- Both Professor Gruber and I cite prior economic studies that conclude that the increase in illicit opioid mortality after 2010 is the consequence of prior shipments and abuse of prescription opioids.[58]

46. The thickening of the market for illicit opioids is further reflected in **Figure 4**, which reports data on seizures of heroin and fentanyl from the National Forensic Laboratory Information System (NFLIS). As the figure indicates, the share of drug seizures involving illicit opioids accelerated after 2010, increasing from less than 7 percent in 2010 to nearly 14 percent by 2017.

Figure 4



[57] Gruber Report, pp. 62-67 and Cutler Report, pp. 36-37.
[58] Gruber Report, pp. 68-69 and Cutler Report, p. 36.

47. Each of these analyses provide strong empirical support that contradicts defendants' characterization that this is an "unsupported" and "made up" theory. All of the evidence described above establishes that the thickening of illicit opioid markets, and the resulting increase in abuse and mortality associated with illicit opioids, was the consequence of defendants' prior misconduct.

48. Defendants further suggest my analysis is somehow unreliable because I "failed to include a control variable for the introduction of illicit fentanyl into illegal drug markets."[59] This reflects a fundamental misunderstanding of the implications of my analysis. As set forth in my March 25 Report, the emergence of heroin and fentanyl was the *consequence* of prior shipments of prescription opioids. As such, it is econometrically inappropriate to include "a control variable for the introduction of illicit fentanyl" in a regression model. A requirement of regression analysis is that "control variables" are "exogenous," which means that it is determined independently of the forces that determine the variable that the regression attempts to explain (here, opioid mortality). In econometric parlance, the "control variable for the introduction of illicit fentanyl" is "endogenous," which means that it is determined in part by opioid mortality and thus not properly considered in the analysis.[60]

49. The analyses I present, along with those from Professor Gruber and other researchers, establish that the emergence of heroin and fentanyl was not "exogenous" but instead resulted from the same forces (shipments of prescription opioids) that drove opioid mortality. The structural break analysis described above establishes that any prior relationship between opioid mortality and the factors that determine it changed fundamentally in 2010 in ways that cannot simply be explained in any other way. Indeed, I understand the Court has even recognized the following:

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[59] Defendants' Daubert Motion, p. 11.

[60] See Joshua D. Angrist and Jorn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, Chapter 4, (Princeton: 2009) for a mostly non-technical discussion of exogenous and endogenous variables in regression analysis.

> When there is a flood of highly addictive drugs into a community it is foreseeable—to the point of being a foregone conclusion—that there will be a secondary, "black" market created for those drugs. It is also foreseeable that local governments will be responsible for combatting the creation of that market and mitigating its effects.[61]

B. There is no basis to defendants' claim that available evidence contradicts the view that the post-2010 illicit opioid crisis is the consequence of the prescription opioid crisis.

50. In responding to my conclusion that the post-2010 illicit opioid crisis was the consequence of the prescription opioid crisis, defendants argue that available data "contradicts Cutler's theory."[62] However, the evidence cited by defendants in support of these claims establishes that defendants' experts misinterpret or mischaracterize available data.

51. Defendants cite changes in heroin prices as a possible alternative explanation for the increase in illicit opioid mortality and defendants' expert Professor Murphy, cited by defendants, also notes that heroin prices started to decline in the 1990s.[63] However, a review of that data is entirely consistent with my conclusion that the post-2010 increase in illicit opioid mortality is due to factors other than changes in heroin prices.

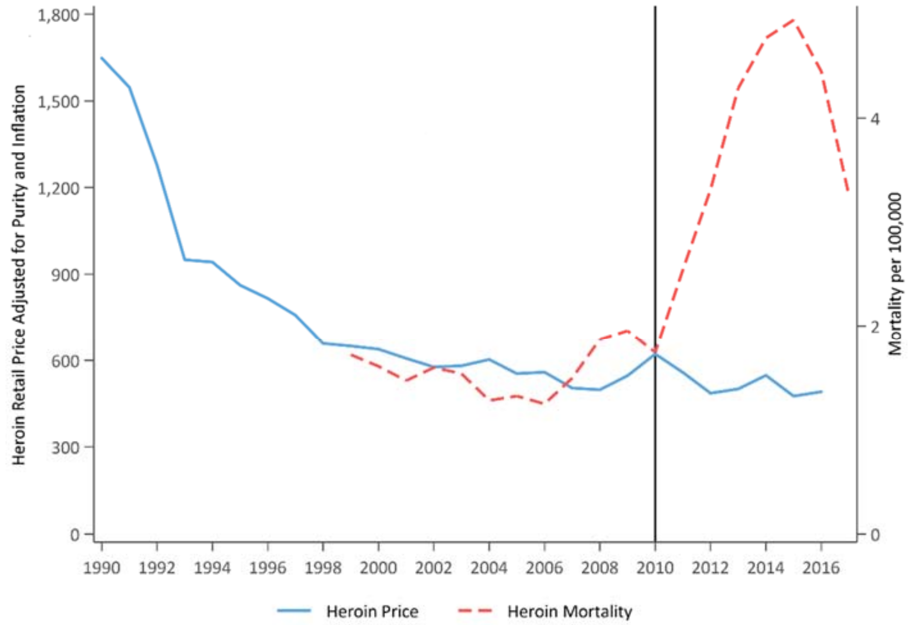
52. **Figure 5** reports estimates of heroin prices in the U.S. from United Nations Office of Drugs and Crime (UNODC) – the same data referred to by Professor Kyle – and identifies a large and long-term decline in heroin prices through the 1990s and 2000s. However, these declines were not associated with an increase in heroin mortality, which is a proxy for heroin abuse. To the contrary, both heroin prices and mortality declined between 1999 and 2006. Indeed, the spike in heroin deaths starting in 2010 is not associated with unusual decreases in heroin prices. Thus, this evidence fails to

[61] Order on Motions to Dismiss (ECF Doc. 1203) at 35.
[62] Defendants' Daubert Motion, p. 11-13. To support these claims, defendants cite the Murphy Report at ¶¶ 161-165.
[63] Murphy Report, ¶ 164.

support the suggestion by defendants and their experts that the post-2010 illicit opioid crisis is due to changes in heroin prices.[64]

Figure 5

Heroin Price and Heroin Mortality Rate: 1990-2016



Source: NCHS Mortality Data, Census Data and UNODC Data

53. The other “contradictory” evidence that defendants suggest rebuts the conclusion of myself and others that the illicit opioid crisis is the consequence of the earlier prescription opioid crisis is Professor Murphy’s analysis of state-level seizures of illicit opioids post-2010. Professor Murphy says that “[i]f, as Professor Cutler asserts, shipments of prescription opioids in the early 2000s led to an increase in the availability of illicit opioids post-2010, I would expect to see at least a correlation between pre-2010 shipments and post-2010 seizures of illicit opioids.”[65] He claims that his analysis

[64] This is consistent with economic literature which has found that changes in heroin prices fail to explain the transition from prescription to illicit opioids after 2010. For example, Alpert, Powell, and Pacula (2018) test whether differences in heroin prices across states can explain differential increases in heroin mortality. They conclude: “We find that state-level heroin price changes are uncorrelated with initial OxyContin misuse, so they are unlikely to explain the differential rise in heroin deaths.” (p. 30)
[65] Murphy Report, p. 101.

indicates that "1997-2010 prescription opioid shipments are not strongly correlated with 2011-16 heroin seizures." [66]

54. As a preliminary observation, the extent of illicit opioid activity can be evaluated more directly using data on illicit opioid mortality instead of data on the share of drug seizures involving heroin. Mortality is directly related to illicit opioid consumption while drug seizures are affected by illicit opioid activity as well as the actions of law enforcement officials, which are driven by a wide variety of unrelated factors such as local policing priorities and resources available to law enforcement. As discussed above, my analysis and that of Professor Gruber establishes that illicit mortality increased more after 2010 in areas with high pre-2010 shipments of prescription opioids, and further established that fentanyl emerged more rapidly in areas that experienced increases in heroin mortality after 2010.

55. Moreover, Professor Murphy mischaracterizes the results of his analysis of the relationship between pre-2010 shipments of prescription opioids and the share of drug seizures involving illicit opioids since 2011. Contrary to claims by defendants and Professor Murphy, his own data show a positive correlation between pre-2010 shipments and drug seizure activity involving illicit opioids since 2011; the correlation coefficient is 0.24, a result that would be observed with only 9 percent probability if in fact there was no relationship between these variables.

56. There are two problems with Professor Murphy's analysis. First, it is more appropriate to test Professor Murphy's hypothesis by comparing pre-2010 prescription opioid shipments to the *change* in the share of seizures accounted for by illicit opioids after 2010. After all, the issue to be explained is the increase in heroin mortality after 2010, not the level of pre-existing heroin mortality. Second, Professor Murphy's measurement of shipments does not use the average per capita shipments in 1997-2010 but instead uses the average of year-specific cumulative averages over this period. He provides no basis for analyzing this metric, which while non-intuitive is nonetheless highly correlated

[66] Murphy Report, p. 102-03.

with average per capita shipments across counties. After making these two modifications to Professor Murphy's analysis – analyzing the change in seizures and using average shipments – the correlation between average shipments from 1997-2010 and the change in heroin's share of seizures rises to 0.28, a result that has less than a 5 percent probability of being observed by chance.[67] If anything, these results establish a statistically significant relationship between pre-2010 shipments of prescription opioids and seizures of illicit opioids.

57. Professor Murphy's data also reveal a strong positive correlation between the change in the share of drug seizures involving heroin in a state between 2011-14 and the change in the share of drug seizures involving fentanyl between 2011-16. This correlation is 0.41 with only a 0.3 percent probability of being observed by chance. This result is consistent with the results discussed by Professor Gruber that established that fentanyl emerged after 2013 in areas with high levels of heroin activity.

58. In sum, the evidence cited by defendants does not contradict my conclusion that the post-2010 illicit crisis was the consequence of prior shipments of opioids by defendants. Instead, they buttress my conclusions.

VI. There is no basis to defendants' claims that my estimates of the share of opioid-related harms attributable to shipments are "speculative and unreliable."

59. Defendants argue that my "estimate of harms attributable to all opioids is based on unreliable data and implicit assumptions."[68] They claim both that my use of mortality as a proxy for other types of opioid-related harms is inappropriate and that a variety of other measures of opioid-

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[67] If Florida, Tennessee and Nevada are excluded from the analysis, then the estimated correlation is 0.38, which would be observed by chance with only 1 percent probability if there was no relationship between these variables. These three states have the highest per capita shipments of prescription opioids and are recognized as transshipment points, which implies that the share of illicit consumption and seizures is likely to be lower in those areas than implied by the level of shipments. For example, 2 of the 4 counties I remove from the large county sample as likely reflecting high levels of transshipments are in Florida and Tennessee.

[68] Defendants' Daubert Motion, p. 16-17.

related harms other than mortality that are used in my analysis are unreliable. There is no basis for any of these claims. I address them in turn.

A. The estimated relationship between shipments and opioid-related mortality is a reliable proxy for the relationship between shipments and other opioid-related harms.

60. As explained in my March 25 Report, my estimates of the share of opioid-related harms that are attributable to shipments of prescription opioids are based on regression estimates of the relationship between shipments and opioid mortality. That is, this element of my analysis uses the relationship between shipments and mortality as a proxy for the relationship between shipments and other opioid-related harms.[69] Defendants claim that this approach is inappropriate and unreliable.[70]

61. Defendants' experts have presented no alternatives to this approach and thus present no analysis that suggests that my analysis yields inflated or misleading estimates of the relationship between shipments and opioid-related harms. In arguing that my approach is unreliable, defendants ignore the fact that mortality data is routinely used by economists to study the harms resulting from use of addictive substances, including alcohol, tobacco, and opioids.[71] Moreover, defendants ignore the supporting analysis of the impact of shipments on crime presented in my initial report.[72] That analysis demonstrates that my use of mortality as a proxy for opioid-related harms is reliable and, if anything, yields a conservative estimate of the impact of shipments on harm for many categories of harm evaluated in my report. That analysis compared estimates of opioid-related crimes attributable to

[69] Cutler Report, p. 13.
[70] Defendants' Daubert Motion, p. 15.
[71] See, for example: John Cawley and Christopher Ruhm, "The Economics of Risky Behaviors," in Mark V. Pauly, Thomas G. McGuire, Pedro P. Barros, ed., *Handbook of Health Economics*, Volume II (2011): 95-199; W. Kip Viscusi & Joni Hersch "The Mortality Cost to Smokers," *Journal of Health Economics*, vol. 27 (2008): 943-958; Christopher Carpenter and Carlos Dobkin, "The Minimum Legal Drinking Age and Public Health," *Journal of Economic Perspectives*, vol. 25, no. 2 (Spring 2011): 133-156; William N. Evans, Ethan Lieber, and Patrick Power, "How the Reformulation of Oxycontin Ignited the Heroin Epidemic," *Review of Economics and Statistics* 101 no. 1 (2019): 1-15 ("Evans, Lieber, and Power (2019)"); Alpert, Powell, and Pacula (2018); David Cutler, Angus Deaton and Adriana Lleras-Muney, "The Determinants of Mortality," *Journal of Economic Perspectives*, Volume 20, Number 3 (Summer 2006): 97-120.
[72] Cutler report, pp. 75-80.

defendants' misconduct based on (i) the mortality-based regression methodologies used in my reported estimates; and (ii) a regression analysis relating crime to shipments – an approach that makes no use of mortality data.

62. Many of the opioid-related harms addressed by Bellwether governments are crime-related, including activities of the sheriff's department, courts, prosecutors, public defenders, and correctional facilities, and my crime regression analysis can be used to approximate the share of harms in these divisions that are opioid-related. As summarized in Table III.17 of my initial report, my analysis indicates that in 2016, 4.4% of crime-related harms in Cuyahoga County and 5.6% of crime-related harms in Summit County were attributable to defendants' misconduct.[73] These figures are based on: (i) the estimated share of crimes that are opioid-related; (ii) the share of harms attributable to shipments of prescription opioids; and (iii) the share of prescription opioids attributable to defendants' misconduct. Step (ii) in this calculation is approximated using regression estimates of the relationship between shipments of prescription opioids and opioid-related mortality.

63. Table III.17 of my initial report also presents an estimate of the percent of crime attributable to defendants' misconduct that is based on my supporting analysis which relies on: (i) regression estimates of the relationship between shipments of prescription opioids and changes in both violent and property crimes; and (ii) the share of prescription opioids attributable to defendants' misconduct.[74] Again, this alternative approach does not involve the use of the estimated relationship between shipments and opioid-related mortality. The supporting analysis indicates that 7.9 percent of crime is attributable to defendants' misconduct.

64. Thus, the crime regression approach yields a higher estimate of the share of crime-related harms due to defendants' misconduct than the approach that utilizes the relationship between

[73] These results are based on "Approach 1" approach. Results based "Approach 2" are nearly identical.
[74] Cutler Report, ¶ 133.

shipments and opioid-related mortality as a proxy. As a result, my estimates of the impact of defendants' misconduct for crime-related harms and damages based on those estimates are lower than would have been estimated based on the crime regression framework.

65. My use of the proxy measure based on mortality allows estimation of harms across multiple categories of harm with a common methodology. Alternative approaches to estimating the relationship between shipments and other opioid-related harms would need to rely on other data sources with well-recognized limitations.

66. The opioid-related mortality data that are used as the basis of my report are used by a wide range of researchers, including defendants' experts, and their overall reliability is not questioned in the research community. These data are available at a county level since 1993. In contrast, other data that might be used to evaluate the relationship between opioid-related harms and shipments have well recognized limitations. As discussed in Professor Gruber's report, data on opioid use disorder (OUD) from the National Survey of Drug Use and Health (NSDUH) are widely recognized to understate opioid abuse.[75] Moreover, these data are available only at the state level, only for 2002-17 and for as few as 17 states in early years. In addition, the NSDUH questionnaire and definition of OUD was changed in 2015, making data for 2015 and more recent years non-comparable to prior data.[76] Data on other harms potentially related to opioids have similar limitations: data on child placements through the foster care system are available for only 2008 to 2017 and only at the state level,[77] and data on opioid-related emergency department visits are available for only 2005 to 2017 and cover as few as 34 states for parts of the sample period.[78]

[75] My analysis of the share of drug crimes that are opioid related utilizes data on the share of individuals with any non-alcohol substance use disorder (SUD) that have OUD. To the extent that OUD is understated relative to other forms of SUD, my analysis is likely to yield understate the extent of opioid-related crime.

[76] Cutler Report, ¶ 23; Gruber Report, pp. 17-20.

[77] https://www.acf.hhs.gov/cb/resource/trends-in-foster-care-and-adoption. Archived versions are available, but only for 2005-2007.

[78] https://www.hcup-us.ahrq.gov/faststats/OpioidUseServlet.

67. As this suggests, my analysis of opioid-related mortality applies the best available data for analyzing the relationship between shipments of prescription opioids on opioid-related harms, and there is no evidence that estimates of the impact of shipments on opioid-related harms based on these data are unreliable or overstated.

B. There is no basis for defendants' claims that the data I use to measure opioid-related harms are unreliable.

68. Defendants argue that my "estimates of the magnitude of economic harms – like crimes, addiction treatments, and juvenile removals" are "speculative and unreliable."[79] I respond to these criticisms immediately below but, as an initial matter, it is important to note that neither defendants nor their experts provide evidence that my analysis yields misleading or overstated estimates of the impact defendants' misconduct.

69. With respect to opioid-related child removals, my analysis is based on data published by the Public Children Services Association of Ohio (PSCAO) which reports the percentage of child removals in which opioids were being used in the home for Cuyahoga and Summit counties.[80] Defendants suggest that this data "does not suggest that the drug use caused the child removal."[81] This claim is simply incorrect.

70. PCSAO Executive Director Angela Sausser testified to the Ohio Senate Health and Medicaid Subcommittee that the survey relied upon was intended to capture the percentage of children who were removed from their home due to opioids. The PSCAO survey focused on removals where parental drug use was a removal factor and then identified which removals were due to opioids. She testified that "a survey my organization conducted showed that half of all children taken into custody in

[79] Defendants' Daubert Motion, p. 17.
[80] See Cutler Report, ¶¶43-44 for a discussion of my method.
[81] Defendants' Daubert Motion, p. 17.

2015 had parental drug use as a removal factor. Of those, more than half had parents using opioids, including heroin. That means 28% of children in custody that year were victims of this epidemic, and that number has almost certainly risen."[82]

71. Defendants claim that my estimates of opioid-related addiction treatments are "speculative and unreliable" but provide no supporting evidence from their own experts or other sources to support this claim.[83] The data I relied on are based on spending for treatment of opioid abuse. The Cuyahoga ADAMHS board reports spending for addiction services separately from spending on mental health services and reports whether "Opioid Abuse/Opioid Type Dependence" is the primary substance use diagnosis for each of individual treated for addiction.[84] The Summit ADM Board's calculations are based on claims data for expenses incurred by individuals with opioid-related diagnosis, which again indicates these are expenses incurred as a result of opioids.[85] The extent to which this spending is related to shipments of prescription opioids is addressed in other elements of my analysis.

72. There is also no basis to defendants' argument that the data on drug-related crimes that I use are unreliable.[86] This element of my analysis relies on a 2011 study from the Department of Justice (DOJ) which relies in part on data from 2002.[87] Defendants and their experts do not show, or even attempt to show, whether this source leads to overestimate or an underestimate of drug-related crimes in Summit or Cuyahoga county. Alternative sources of crime data suggested by defendants' expert Mr. Bialecki do not contain information on whether an incident was motivated by drug use (e.g. to obtain money for drugs) which are included in the estimates of drug-related crimes used in my analysis.[88] Thus,

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[82] http://advocatesforohio.org/perch/resources/PCSAO-Subcommittee-Testimony.pdf
[83] Defendants' Daubert Motion, p. 17.
[84] See, e.g., 2017 ADAMHS Annual Report at p. 8, 11.
[85] SUMMIT_001146951
[86] Defendants' Daubert Motion, p. 17.
[87] US DOJ National Drug Intelligence Center, "The Economic Impact of Illicit Drug Use on American Society" (2011), Table 1.7.
[88] The only defendant expert to offer alternative calculations to the percent of crimes that are drug-related is Mr. Bialecki (see Expert Report of Matthew G. Bialecki, CPA, CFF, CGMA, May 10, 2019, ("Bialecki Report"), pp. 172-

the data I use provide a more reliable estimate of the overall percentage of crime categories that are drug-related.

73. My analysis of the share of drug-related crimes that are attributable to opioids follows the approach used by Florence, et al. (2016), Birnbaum, et al. (2011), Hansen, et al. (2011), Birnbaum, et al. (2006) and other published academic literature.[89] Defendants provide no evidence why the approach used in these peer-reviewed published studies is unreliable, nor does any defense expert suggest any other data that would be reliable or yield different answers.

VII. There is no basis to defendants' claims that my use of ARCOS results in a "critical mismatch" with Professor Rosenthal's analysis and yields unreliable results.

74. Defendants argue that there is a "critical mismatch" between my analysis, which relies on county-level data on shipments of prescription opioids measured in morphine milligram equivalent units (MMEs), and Professor Rosenthal's, which relies in part on national data on prescriptions, also measured on an MME basis.[90] Referring to Professor Kyle's report, defendants argue that "[r]eplacing

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174). He reports alternative calculations based on the Cuyahoga Prosecutors' data (that I use in my estimation to calculate the counts of different criminal activity in Cuyahoga) and data from the FBI's National Incident-Based Reporting System (NIBRS). The NIBRS data contain information on whether drugs were seized during an incident and information on whether the reporting officer suspected the offenders of using drugs during the incident (see Criminal Justice Information Services Division Uniform Crime Reporting Program, 2019 National Incident-Based Reporting System User Manual 03/30/2018, p. 74 and p. 93). Mr. Bialecki's alternative calculation using the Cuyahoga Prosecutor's data is based on identifying drug-related keywords in two different fields that contain labels for the offense charged (Bialecki report, Table VIC-6 notes for a description of his method). Both of these data sources are limited to identifying drug-related crimes to instances in which drugs and/or drug use is observed during the incident and, therefore would not identify crimes committed for the purpose of obtaining money for drugs or other possible drug-related motivations.

[89] See: Florence, Curtis S., Chao Zhou, Feijun Luo, and Likang Xu. "The economic burden of prescription opioid overdose, abuse, and dependence in the United States, 2013." *Medical Care* 54 (2016); Birnbaum, Howard G., Alan G. White, Matt Schiller, Tracy Waldman, Jody M. Cleveland, and Carl L. Roland. "Societal costs of prescription opioid abuse, dependence, and misuse in the United States." *Pain medicine* 12, no. 4 (2011): 657-667; Hansen, Ryan N., Gerry Oster, John Edelsberg, George E. Woody, and Sean D. Sullivan. "Economic costs of nonmedical use of prescription opioids." *The Clinical journal of pain* 27, no. 3 (2011): 194-202; and Birnbaum, Howard G., Alan G. White, Jennifer L. Reynolds, Paul E. Greenberg, Mingliang Zhang, Sue Vallow, Jeff R. Schein, and Nathaniel P. Katz. "Estimated costs of prescription opioid analgesic abuse in the United States in 2001: a societal perspective." *The Clinical journal of pain* 22, no. 8 (2006): 667-676.

[90] Defendants' Daubert Motion, p. 16.

Cutler's shipment data with Rosenthal's prescription data reduces Cutler's 'average impact' percentage by 50 percent."[91]

75. This section shows: (i) that my use of shipments data is appropriate; (ii) that defendants mischaracterize Professor Kyle's analysis and results, which contain fundamental errors; and (iii) that the use of an alternative source of opioid prescription rates published by the CDC does not materially affect my results.

76. First, analysis based on shipments data is appropriate, and defendants do not suggest otherwise. Defendants' focus instead is on their claim that the use of prescription level data yields an estimated relationship with opioid-related mortality that, while still statistically significant, is smaller than that based on shipments. The relevant question is which provides the more reliable county-level estimates of prescription drug activity in the counties in the analysis: the ARCOS data or the prescription data.

77. The DEA's ARCOS database that I use is comprehensive and accounts for all shipments of prescription opioids into a county in a given year. None of defendants' experts challenge the reliability of the ARCOS data, which are commonly used in the economics literature.[92] In contrast, the MME-adjusted prescription-level data used by Professor Kyle provide an incomplete measure of opioid shipments because these data fail to account for opioids that are diverted or stolen, or that do not go through retail distribution channels.[93] The prescription data used by Professor Kyle are from a sample that are extrapolated to totals based on a "patented projection methodology."[94] ARCOS, in contrast,

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[91] Defendants' Daubert Motion, p. 16.
[92] See: Alpert, Powell, and Pacula (2018); Evans, Lieber, and Power (2019).
[93] This limitation is acknowledged by Professor Kyle. Expert Report of Margaret K. Kyle, May 10, 2019 ("Kyle Report"), ¶¶ 176-177.
[94] https://gis.cdc.gov/grasp/PSA/Downloads/OAU-Data-Methods.pdf

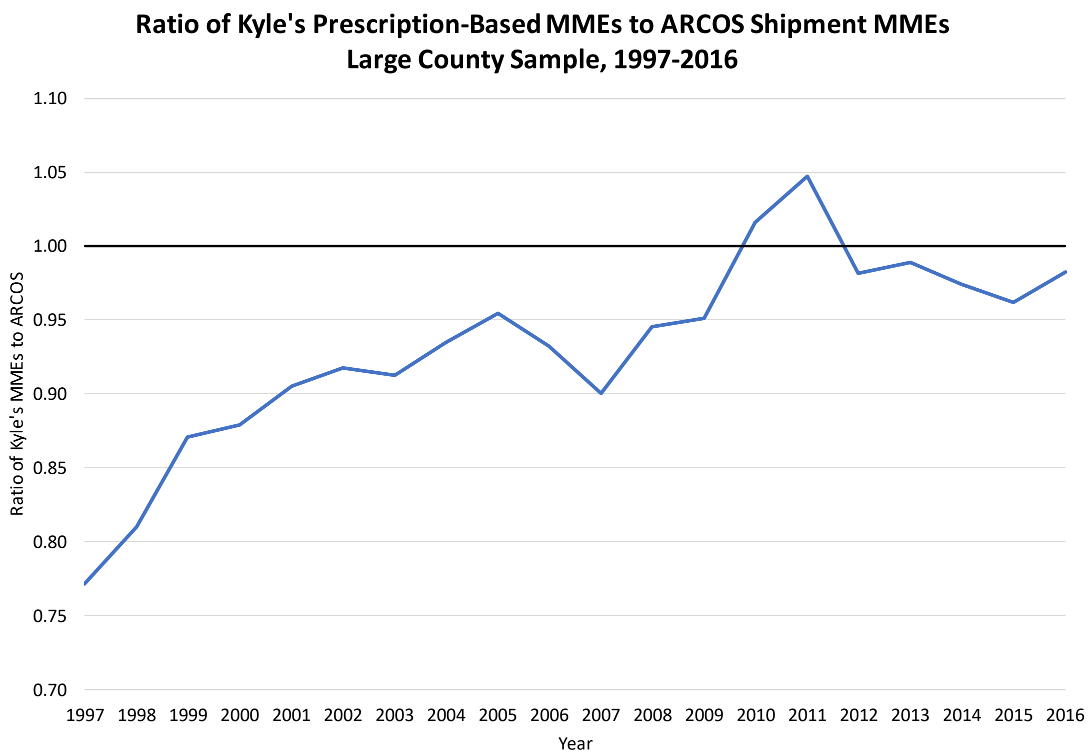
provides a complete census of shipments of prescription opioids. There is no reason to use data from an extrapolated sample when a complete census is available.

78. Defendants' claim that my analysis "mixes apples and oranges" because Professor Rosenthal uses data based on prescription activity is misleading, as is defendants' claim that Professor Kyle simply "[replaced] Cutler's shipment data with Rosenthal's prescription data".[95] Professor Rosenthal relies on the IQVIA National Prescription Audit (NPA) database, which is national time series data on a sample of prescription-based MMEs.[96] In contrast, Professor Kyle's analysis relies on the IQVIA Xponent database, which is based on a sample of prescription activity by physicians and extrapolated based on a "patented projection methodology."[97] Thus, Professor Kyle did not simply replace the ARCOS shipment data with "Rosenthal's prescription data."[98]

79. Review of the data shows that the data analyzed by Professor Kyle differ from the ARCOS data in key ways. **Figure 6** summarizes the ratio of annual MMEs per capita per day from the IQVIA Xponent data as constructed by Professor Kyle to the ARCOS data for the large county sample. The IQVIA Xponent data generate consistently lower estimates of MMEs per capita than in ARCOS. For example, the difference is more than 20 percent in the early part of the sample period. Further, the IQVIA Xponent data suggest that MMEs per capita grew more rapidly than per capita shipments measured by ARCOS: 624 percent versus 450 percent between 1997 and 2010. Moreover, the IQVIA Xponent data suggest that there was a 17 percent increase in MMEs per capita between 2009 and 2010, compared to 9 percent for the ARCOS data. These differences may reflect the fact that the IQVIA Xponent data are based on a sample which is extrapolated, while the ARCOS data measure all shipments based on a census.

[95] Defendants' Daubert Motion, p. 16.
[96] Expert Report of Professor Meredith Rosenthal, March 25, 2019, ("Rosenthal Report"), ¶ 51.
[97] https://gis.cdc.gov/grasp/PSA/Downloads/OAU-Data-Methods.pdf
[98] Defendants' Daubert Motion, p. 16.

Figure 6



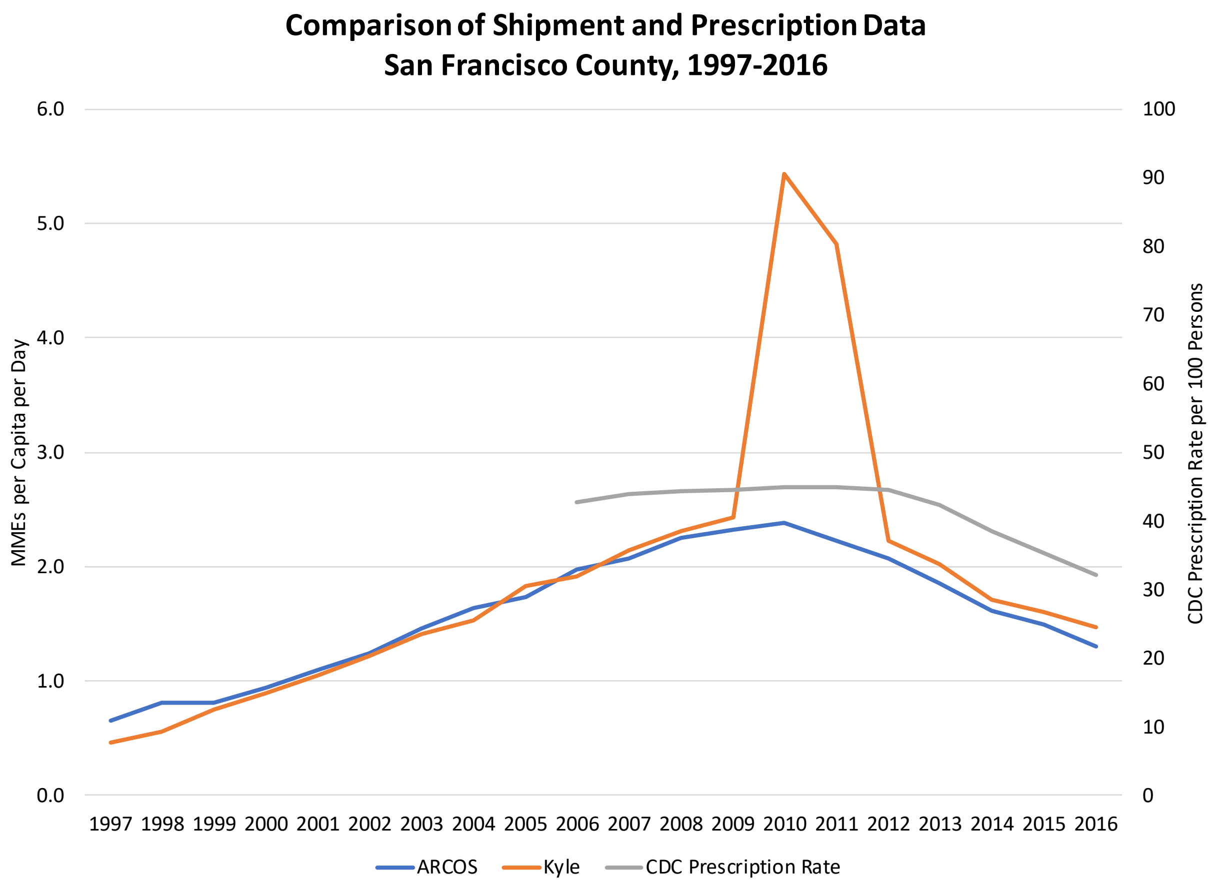
Source: ARCOS; Kyle backup materials.

80. A cursory review of county-level IQVIA Xponent data as reported in Professor Kyle's work papers identified numerous irregularities in Professor Kyle's data that strongly suggest measurement errors. For example, for a substantial number of counties, Professor Kyle's data exhibit large increases in prescriptions in one year, only to be reversed one or two years later – outliers that are nowhere apparent in the data from ARCOS or in data on prescription activity from the Centers for Disease Control. **Figure 7.1** reports MMEs per capita per day for San Francisco County for 1997 through 2016 based on ARCOS and as constructed by Professor Kyle from the IQVIA Xponent data. The figure also reports opioid prescription rates per 100 persons from publicly available data from the CDC, which is based on the same IQVIA data as relied on by Professor Kyle.[99] Professor Kyle's data suggest that

[99] https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html. This series is plotted on the secondary Y-axis because the CDC reports rates of prescription per 100 persons, not MMEs.

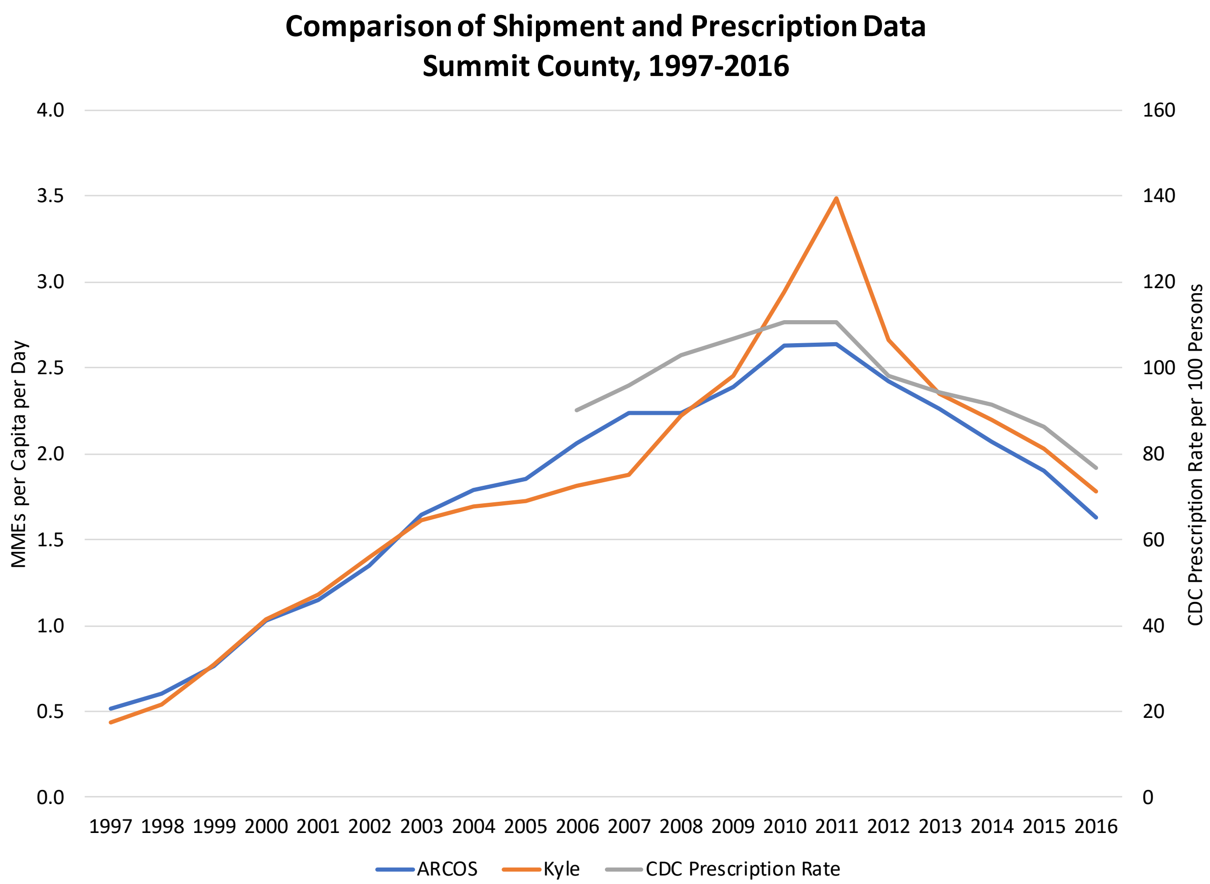
prescription MMEs increased by more than 120 percent between 2009 and 2010, before falling again after 2011. Neither the ARCOS data nor the CDC data show such a jump.

Figure 7.1



81. **Figure 7.2** presents similar information for Summit County. Professor Kyle's data suggest that MMEs increased by 20 percent in Summit between 2009 and 2010, while the ARCOS data indicate that MMEs increased by only 10 percent and the CDC data indicate that prescription activity increased by less than 4 percent.

Figure 7.2



82. Similar irregular shipment increases, followed by irregular declines, are observed in more than 20 counties in Professor Kyle's data between 2009 and 2012.

83. These irregularities, combined with the inherent measurement error from having only a sample of shipments and an incomplete set of shipment channels, appear to lead to significant measurement error in the data used by Professor Kyle. As one example of this, the variance in prescription-based MMEs per capita across counties in Professor Kyle's sample is substantially wider than that based on ARCOS data. For example, **Table 4** indicates that the gap between counties at the 5th and 95th percentile of county-specific values of MMEs per capita was 1.47 based on ARCOS and 2.05

based on Professor Kyle's IQVIA Xponent data. That is, the county-specific variation in the IQVIA Xponent data was 39 percent higher than observed based on ARCOS.

Table 4

Distribution of MMEs per Capita per Day Across Counties
ARCOS vs. Kyle IQVIA Data

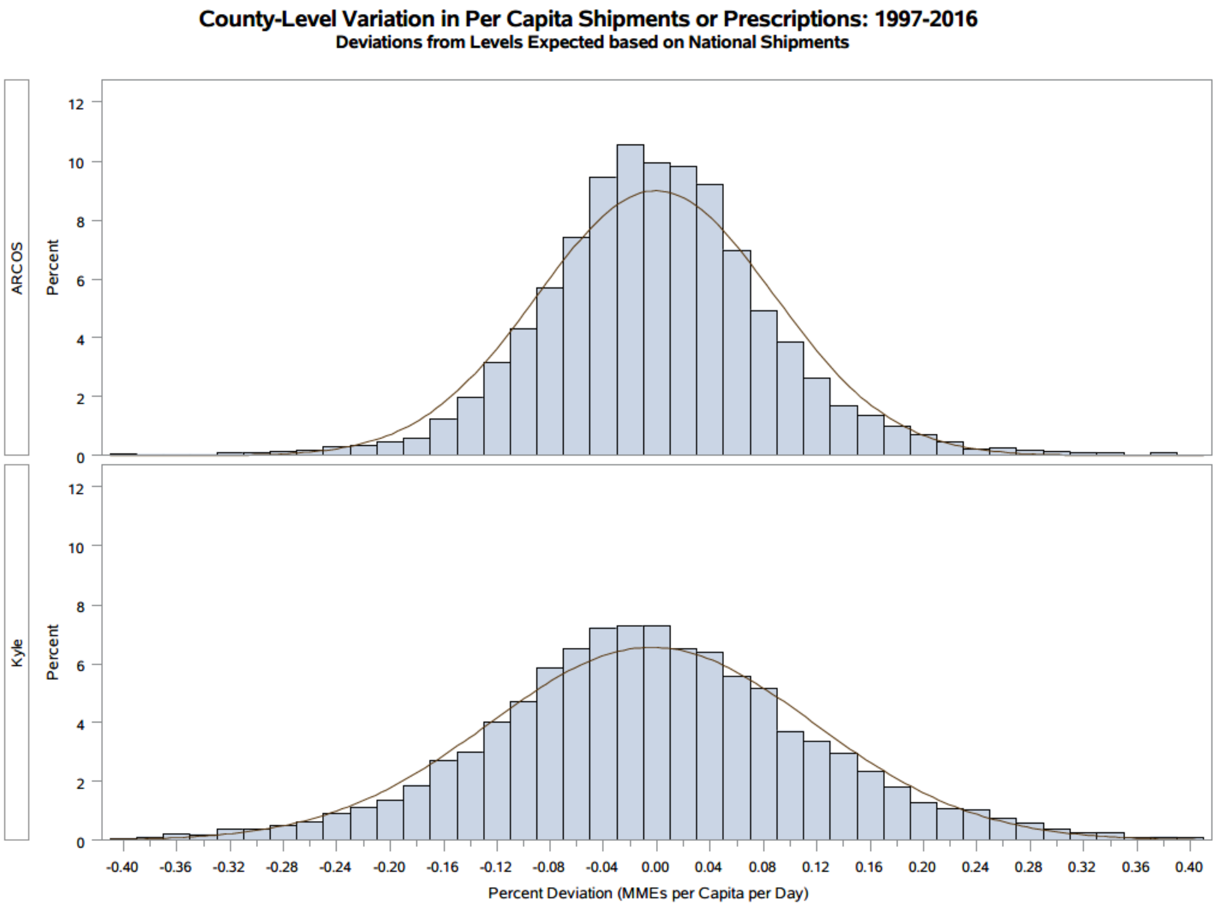
Source	Mean	p5	p25	p50	p75	p95	Range p5-p95
ARCOS	1.45	0.81	1.11	1.40	1.75	2.28	1.47
Kyle	1.35	0.55	0.89	1.23	1.66	2.60	2.05

Note: Based on large county sample, shipments/prescriptions from 1997-2010.

84. An alternative approach to measuring the extent of potential measurement error in Professor Kyle's data is to evaluate how much shipments or prescription activity deviates from levels expected based on national trends. A wider range of deviations between actual and expected levels of activity is indicative of greater measurement error in the underlying data. I estimate expected shipments or prescription activity using a regression relating the logarithm of county-level shipments/prescription activity to county dummy variables and the logarithm of national shipments/prescription activity, allowing for a different effect of national shipments/prescription activity in each county. Larger patterns of deviations from expected levels measured in this way are indicative of greater measurement error in the underlying data.

85. The results of this analysis are summarized graphically in **Figure 8** and **Table 5**. The deviation between actual and expected county-level prescription activity based on Professor Kyle's data is substantially wider than that based on ARCOS shipments data, indicating that Professor Kyle's data are subject to greater measurement error. **Table 5** shows that the range between the 5th and 95th percentile of these distribution is 53 percent wider for Professor Kyle's IQVIA Xponent measure compared to that based on ARCOS.

Figure 8



Source: ARCOS; Kyle production.

Table 5

Distribution of County-Level Variation in Per Capita Shipments or Prescriptions
ARCOS vs. Kyle IQVIA Data

Source	Mean	p5	p25	p50	p75	p95	Range p5-p95
ARCOS	0.00	-0.14	-0.05	0.00	0.05	0.15	0.28
Kyle	0.00	-0.21	-0.08	-0.01	0.07	0.22	0.43

Note: Based on large county sample, shipments/prescriptions from 1997-2016.

86. Each of these analyses indicate that the IQVIA Xponent data as constructed by Professor Kyle are subject to greater measurement error than ARCOS data. As discussed above, errors in the measurements of independent variables in a regression (such as prescriptions or shipments) typically

result in estimates that understate true relationships (here, between opioid availability and opioid-related mortality). This almost certainly explains why Professor Kyle's regressions yield lower estimates than do the ones I presented. Nonetheless, even the data that Professor Kyle presents still yield a significant positive relationship between prescription opioid MMEs and changes in opioid mortality in the large county sample.

87. In sum, the differences in the estimates of the magnitude of the relationship between shipments of prescription opioids and opioid-related mortality between Professor Kyle's analysis and my own do not indicate that my analysis is unreliable, as defendants suggest.[100] Instead, it raises fundamental questions about the reliability of the results presented by Professor Kyle.

88. In order to further test the sensitivity of my analysis to the use of data on opioid prescriptions, I have estimated an alternative model which relies on the publicly available data from the CDC on opioid prescription rates per county from 2006-2010. In contrast to the ARCOS and IQVIA Xponent data, this measure of prescription opioid activity is not weighted by MMEs and covers a shorter time period. Still, it is a useful comparison.

89. This alternative prescription-based regression generates a large and statistically significant estimate of the relationship between prescriptions and changes in opioid mortality in the large county sample. **Table 6** reports the impact of prescription activity on opioid mortality from 2006-2010 implied by this alternative regression.[101] This table is parallel to that presented in Appendix Table I.1 from my initial report. The estimated impact of prescriptions on opioid mortality from this model is larger than that based on ARCOS data used in my initial report and much larger than that reported by Professor Kyle.

[100] Defendants' Daubert Motion, p. 16.

[101] The CDC prescription rate data are available by county beginning in 2006. The data report the rate of opioid prescriptions per 100 persons by county and year and are not expressed in MMEs.

Table 6

Percent of Any Opioid Mortality Attributable to Prescription Rate Based on Direct Regression
2006-2010

Year	Actual Mortality	Cumulative Average Prescriptions	Prescription Coefficient from Regression	Impact on Mortality	But-For Mortality	Percent Impact on Mortality
	A	*B*	*C*	*D = B * C*	*E = A - D*	*F = D / A*
2006	10.03	2.00	3.08	6.18	3.85	**61.6%**
2007	10.56	2.05	3.08	6.32	4.25	**59.8%**
2008	11.13	2.08	3.08	6.42	4.70	**57.7%**
2009	11.52	2.11	3.08	6.50	5.03	**56.4%**
2010	11.77	2.13	3.08	6.57	5.20	**55.8%**

90. These results show that analysis based on appropriately measured prescription activity yields results that are similar to or larger than those presented in my report. Again, these results contradict defendants' claim that my analysis is unreliable.

David M. Cutler

July 31, 2019

Appendix A

Table A.1: Percent of Shipments Attributable to Distributors' Misconduct

Year	Percent of Shipments Attributable to Distributors' Misconduct
1997	41.4%
1998	56.3%
1999	56.4%
2000	51.8%
2001	54.2%
2002	51.0%
2003	57.9%
2004	56.1%
2005	57.1%
2006	64.4%
2007	73.6%
2008	76.2%
2009	72.4%
2010	74.8%
2011	78.3%
2012	79.5%
2013	69.6%
2014	76.3%
2015	82.9%
2016	80.6%

Source: Supplemental Expert Report of Craig J. McCann, Ph.D., CFA, April 3, 2019, Table A, p. 2

Table A.2: Percent of Harms Attributable to Distributors' Misconduct Under Approach 1
2006 – 2016

	Any Opioid			Licit (Rx + Methadone)			Illicit (Heroin + Fentanyl)			Total			
Year	Actual Mortality	Impact on Mortality	But-For Mortality	Actual Mortality	Impact on Mortality	But-For Mortality	Actual Mortality	Impact on Mortality	But-For Mortality	Actual Mortality	Impact on Mortality	But-For Mortality	Percent Impact
	A	*B*	*C = A - B*	*D*	*E*	*F = D - E*	*G*	*H*	*I = G - H*	*J*	*K*	*L = J - K*	*M = K / J*
2006	9.97	2.76	7.21							9.97	2.76	7.21	**27.7%**
2007	10.51	3.12	7.39							10.51	3.12	7.39	**29.7%**
2008	11.06	3.47	7.59							11.06	3.47	7.59	**31.4%**
2009	11.45	3.77	7.68							11.45	3.77	7.68	**32.9%**
2010	11.66	4.09	7.57							11.66	4.09	7.57	**35.1%**
2011				8.23	2.97	5.27	3.80	1.61	2.19	12.03	4.58	7.45	**38.1%**
2012				7.47	3.15	4.32	4.55	2.25	2.30	12.02	5.40	6.62	**44.9%**
2013				6.92	3.26	3.66	5.65	3.08	2.57	12.57	6.34	6.23	**50.5%**
2014				6.57	3.37	3.19	7.28	4.33	2.95	13.85	7.70	6.14	**55.6%**
2015				6.05	3.49	2.56	9.22	5.81	3.41	15.27	9.30	5.97	**60.9%**
2016				5.91	3.56	2.35	12.20	8.00	4.20	18.11	11.56	6.55	**63.8%**

Table A.3: Percent of Harms Attributable to Distributors' Misconduct Under Approach 2
2006 – 2016

Year	Actual Mortality	Predicted Mortality	Percent Impact of All Shipments	Weighted Average Cumulative Percent of Shipments Attributable to Defendants' Misconduct	Percent Impact
	A	*B*	*C = (A - B) / A*	*D*	*E = C * D*
2006	8.46	1.38	83.7%	56.2%	**47.1%**
2007	9.13	1.31	85.6%	59.0%	**50.5%**
2008	9.83	1.45	85.2%	61.4%	**52.3%**
2009	9.69	2.22	77.1%	62.8%	**48.5%**
2010	10.23	2.27	77.8%	64.3%	**50.0%**
2011	11.44	2.04	82.2%	65.9%	**54.2%**
2012	11.62	1.85	84.1%	67.3%	**56.6%**
2013	12.31	1.73	85.9%	67.5%	**58.0%**
2014	13.75	1.51	89.0%	68.2%	**60.7%**
2015	15.39	1.38	91.1%	69.2%	**63.0%**
2016	18.46	1.33	92.8%	69.9%	**64.9%**

Table A.4: Share of Cuyahoga Opioid Harms Due to Distributors' Misconduct

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Approach 1													
ADAMHS Board	0.9%	1.1%	1.4%	1.4%	1.5%	1.6%	1.8%	3.5%	4.0%	5.4%	7.8%	8.9%	8.9%
DCFS	1.3%	1.6%	1.9%	2.3%	2.6%	2.8%	3.3%	4.5%	5.6%	6.7%	9.5%	10.0%	10.0%
Office of Prosecutor	1.5%	1.6%	2.3%	2.8%	3.4%	3.7%	4.4%	5.1%	5.2%	5.3%	5.8%	7.0%	7.0%
Office of Public Defender	1.5%	1.6%	2.3%	2.8%	3.4%	3.7%	4.4%	5.1%	5.2%	5.3%	5.8%	7.0%	7.0%
Court of Common Pleas	1.6%	1.7%	2.3%	2.8%	3.5%	3.8%	4.6%	5.5%	5.8%	5.9%	6.4%	7.8%	7.8%
Juvenile Court	0.5%	0.5%	0.7%	0.8%	0.8%	0.9%	1.0%	1.4%	1.9%	1.9%	2.8%	2.8%	2.8%
Sheriff's Office	1.5%	1.6%	2.3%	2.8%	3.4%	3.7%	4.4%	5.1%	5.2%	5.3%	5.8%	7.0%	7.0%
County Jail	1.5%	1.6%	2.3%	2.8%	3.4%	3.7%	4.4%	5.1%	5.2%	5.3%	5.8%	7.0%	7.0%
Office of Medical Examiner	2.5%	2.5%	3.8%	4.9%	6.0%	8.1%	9.7%	12.5%	13.6%	14.3%	24.2%	24.5%	24.5%
Approach 2													
ADAMHS Board	1.5%	2.0%	2.3%	2.1%	2.2%	2.2%	2.3%	4.0%	4.4%	5.5%	7.9%	9.1%	9.1%
DCFS	2.1%	2.7%	3.2%	3.4%	3.7%	4.0%	4.1%	5.1%	6.1%	6.9%	9.7%	10.2%	10.2%
Office of Prosecutor	2.6%	2.8%	3.8%	4.1%	4.8%	5.2%	5.6%	5.8%	5.7%	5.5%	5.9%	7.1%	7.1%
Office of Public Defender	2.6%	2.8%	3.8%	4.1%	4.8%	5.2%	5.6%	5.8%	5.7%	5.5%	5.9%	7.1%	7.1%
Court of Common Pleas	2.7%	2.8%	3.8%	4.2%	4.9%	5.4%	5.8%	6.3%	6.3%	6.1%	6.5%	7.9%	7.9%
Juvenile Court	0.8%	0.9%	1.2%	1.1%	1.2%	1.3%	1.3%	1.6%	2.0%	2.0%	2.8%	2.8%	2.8%
Sheriff's Office	2.6%	2.8%	3.8%	4.1%	4.8%	5.2%	5.6%	5.8%	5.7%	5.5%	5.9%	7.1%	7.1%
County Jail	2.6%	2.8%	3.8%	4.1%	4.8%	5.2%	5.6%	5.8%	5.7%	5.5%	5.9%	7.1%	7.1%
Office of Medical Examiner	4.3%	4.3%	6.3%	7.2%	8.6%	11.5%	12.2%	14.4%	14.8%	14.8%	24.6%	24.9%	24.9%

Table A.5: Share of Summit Opioid Harms Due to Distributors' Misconduct

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Approach 1													
ADM Board	0.5%	0.6%	0.7%	0.9%	2.1%	2.1%	3.7%	6.1%	7.0%	8.0%	9.8%	8.8%	8.8%
Children Services Board	1.2%	1.5%	2.0%	2.9%	7.7%	8.1%	10.5%	12.4%	13.4%	15.2%	19.4%	17.2%	17.2%
Prosecutor	1.5%	1.5%	2.1%	2.6%	2.8%	3.4%	4.3%	4.7%	5.6%	7.0%	7.6%	7.5%	7.5%
Court of Common Pleas	1.5%	1.5%	2.1%	2.6%	2.8%	3.4%	4.3%	4.7%	5.6%	7.0%	7.6%	7.5%	7.5%
Juvenile Court	0.7%	0.8%	1.1%	1.3%	1.6%	1.9%	2.4%	2.5%	2.9%	3.4%	4.3%	4.2%	4.2%
Sheriff's Office	1.5%	1.5%	2.1%	2.6%	2.8%	3.4%	4.3%	4.7%	5.6%	7.0%	7.6%	7.5%	7.5%
County Jail	1.5%	1.6%	2.2%	2.6%	3.1%	3.3%	3.9%	4.5%	5.1%	5.7%	6.0%	6.0%	6.0%
Alternative Corrections	1.5%	1.6%	2.2%	2.6%	3.1%	3.3%	3.9%	4.5%	5.1%	5.7%	6.0%	6.0%	6.0%
Adult Probation	1.5%	1.5%	2.1%	2.6%	2.8%	3.4%	4.3%	4.7%	5.6%	7.0%	7.6%	7.5%	7.5%
Medical Examiner	3.0%	3.1%	3.0%	4.4%	5.4%	4.8%	7.9%	7.8%	13.0%	16.4%	23.6%	20.4%	20.4%
Approach 2													
ADM Board	0.8%	1.0%	1.2%	1.4%	2.9%	3.0%	4.6%	7.0%	7.7%	8.3%	9.9%	8.9%	8.9%
Children Services Board	2.0%	2.6%	3.4%	4.3%	11.0%	11.5%	13.2%	14.3%	14.6%	15.8%	19.7%	17.5%	17.5%
Prosecutor	2.5%	2.5%	3.4%	3.9%	4.0%	4.9%	5.4%	5.4%	6.1%	7.2%	7.7%	7.7%	7.7%
Court of Common Pleas	2.5%	2.5%	3.4%	3.9%	4.0%	4.9%	5.4%	5.4%	6.1%	7.2%	7.7%	7.7%	7.7%
Juvenile Court	1.2%	1.4%	1.8%	1.9%	2.2%	2.7%	3.0%	2.9%	3.2%	3.5%	4.4%	4.2%	4.2%
Sheriff's Office	2.5%	2.5%	3.4%	3.9%	4.0%	4.9%	5.4%	5.4%	6.1%	7.2%	7.7%	7.7%	7.7%
County Jail	2.6%	2.7%	3.6%	3.8%	4.4%	4.7%	4.9%	5.2%	5.5%	5.9%	6.1%	6.1%	6.1%
Alternative Corrections	2.6%	2.7%	3.6%	3.8%	4.4%	4.7%	4.9%	5.2%	5.5%	5.9%	6.1%	6.1%	6.1%
Adult Probation	2.5%	2.5%	3.4%	3.9%	4.0%	4.9%	5.4%	5.4%	6.1%	7.2%	7.7%	7.7%	7.7%
Medical Examiner	5.2%	5.3%	5.0%	6.5%	7.7%	6.8%	10.0%	9.0%	14.1%	17.0%	24.0%	20.7%	20.7%